SuN Soziologie und Nachhaltigkeit
Beiträge zur sozial-ökologischen Transformationsforschung

01/2025

Who is ready to support the German energy transition?

An explorative longitudinal analysis of determinants of attitudes towards renewables

Marco Sonnberger / Thomas Krause / Michael Ruddat

Zusammenfassung: Die Energiewende in Deutschland ist ein komplexer Prozess der unter anderem von öffentlichen Debatten und unterschiedlichen Meinungen beeinflusst wird. Auch deshalb hat sich die sozialwissenschaftliche Energieforschung mit den Einstellungen der Bürger*innen gegenüber Energieinfrastrukturen und Energiepolitik befasst. In diesem Zusammenhang behandelt unser Artikel zwei Forschungslücken: a) die Untersuchung von möglichen Gruppenunterschieden in den Einstellungen gegenüber der Energiewende und b) eine Analyse der zeitlichen Entwicklung der Einstellungen gegenüber der Energiewende. Diese werden anhand von Längsschnittdaten aus dem GESIS Panel und einer innovativen Kombination von Strukturgleichungsmodellierung (SEM) und maschinellen Lernmodellen (SEM Trees basierend auf einem latent growth curve model, LGCM) bearbeitet. Unsere Analysen zeigen, dass die Einstellungen über die Zeit hinweg relativ stabil sind und neben Bildung und dem Haushaltsnettoeinkommen insbesondere eine ökologische Wertorientierung (gemessen durch die Skala des New Ecological Paradigm) für die Identifikation von Subgruppen mit unterschiedlichen Einstellungen gegenüber der Energiewende relevant ist.

Abstract: The transformation of the energy system is a complex process that is significantly influenced, among other factors, by public resonances, debates and opinion structures. Research into citizens' attitudes towards energy infrastructures and policies has therefore become an important focus of social science energy research in Germany and beyond. In this context, this article aims to address the following two research gaps: a) exploring potential variations in attitudes towards the German energy transition between social groups, and b) analyzing the development of attitudes towards the German energy transition over time. We draw on longitudinal data from the GESIS Panel and employ a fairly novel combination of structural equation modeling (SEM) and machine learning models, namely SEM Trees based on a latent growth curve model (LGCM). Our analysis shows that attitudes towards the energy transition are notably stable over time and exhibit only minimal changes. The SEM Tree approach reveals that an ecological worldview in particular (measured by the New Ecological Paradigm scale), alongside education level and household net income are the most relevant variables for identifying subgroups with distinct perception profiles regarding the German energy transition.

Introduction

The German energy transition is a sociotechnical project with large-scale impacts on the lifeworlds of citizens. Energy policies, local energy projects and the overall aims of the energy transition are therefore the topic of ongoing public debate and are contested from different sides both in Germany and beyond. Accordingly, the formation, structure and consequences of public opinions towards energy transitions has become an important field of study for the social sciences (Sovacool 2014). There is a huge body of research on factors influencing the acceptance of different (renewable) energy technologies (e.g. Devine-Wright 2005; Jones/Eiser 2009; Rand/Hoen 2017; Walter/Gutscher 2013; Sonnberger/Ruddat 2017, 2018). There is also a considerable number of studies focusing on public support for or opposition to specific energy policies (e.g. Setton 2019; Levi et al. 2023; Steentjes et al. 2017; Wolf et al. 2022, 2023). Research on local conflicts concerning siting decisions (e.g. Aitken 2010; Reusswig et al. 2016) and on the public perception of and resonances towards regional structural change in the context of energy transitions (e.g. Gürtler et al. 2021; Haas et al. 2022; Gürtler/Herberg 2023) is also plentiful. However, there is less research on the structures of the public perception of energy transitions in general. Where there are studies, they mainly focus on the influence of cost-benefit perceptions, trust in key actors, place attachment and environmental concern on attitudes towards energy sources (for an overview, see Boudet 2019). However, the impact of sociodemographics, patterns of social inequality and basal attitudinal characteristics such as democratic orientations remains poorly understood (e.g. Lux et al. 2022; Sommer et al. 2022; Judge et al. 2023). This is all the more surprising given that in the public debate around the German energy transition, arguments are repeatedly brought forward indicating that it is the "old conservative males," the rural population, the "economically deprived" or the "working class" who are skeptical of renewables, and of climate protection and mitigation in general. It also seems reasonable to assume that public opinions about renewables are highly influenced by certain events and subsequent public debates, and thus may vary over time and within specific social groups. A recent prominent example of events which triggered public debates about energy is Putin's war on Ukraine. Germany, as well as other European countries, had to face the discontinuation of Russian gas and oil imports just a few months before winter 2022/23. The public debate at the time focused on questions of energy scarcity, energy security, energy justice and possible energy savings. However, it remains unclear how such events have influenced attitudes towards the German energy transition among different social groups. To date, no systematic longitudinal analysis of the variations in public opinions towards the German energy transition exists. With our analysis, we thus aim to address the following two research gaps: a) understanding potential variations in attitudes towards the energy transition in Germany between social groups, and b) understanding the development of attitudes towards the energy transition over time. The following research questions form the starting point for our research:

1. Is it possible to identify social groups with distinct characteristics that vary systematically with regard to their attitude towards the German energy transition?

2. Does public opinion towards the German energy transition vary over time? If so, is there variation in the attitudes towards the German energy transition among specific social groups?

As the open formulation of our research questions suggests, we take an explorative research approach. To answer these research questions, we draw on longitudinal data from the GESIS Panel and employ a modern combination of structural equation modeling (SEM) and machine learning models, namely SEM Trees (Brandmaier et al. 2013; Brandmaier/Jacobucci 2023) based on a latent growth curve model (LGCM). LGCM-based SEM Trees leverage the modeling advantages of LGCMs and combine them with flexible, data-driven decision tree analysis to inductively identify subgroups with different growth trajectories based on covariates. This analysis method allows for the exploratory, data-driven uncovering of previously non-specified, non-linear, non-additive and non-monotonic relationships.

This article is structured as follows: in the next section, we give an overview of the state of research concerning different aspects of public opinion on the energy transition in Germany. We then illustrate our methodological approach, data base and applied measures. We go on to present our results and subsequently discuss them with regard to their contribution to the state of research and also their practical implications. We then conclude with a discussion of the shortcomings of our study and recommendations for future research.

1. State of research

In Germany, there is extensive monitoring of public opinion on the energy transition through regular surveys such as the GESIS Panel, the Social Sustainability Barometer of the Energy Transition and the Environmental Awareness Study commissioned by the German Environment Agency (German: Umweltbundesamt). All of these surveys show the same results: the German public largely approves of the energy transition and renewable energies in general (BMU/UBA 2019; BMUV/UBA 2023; Setton 2019; Sonnberger/Ruddat 2016, 2018; Wolf et al. 2022, 2023). The level of acceptance is thus quite high. This overall support is also relatively stable across time (see e.g. BMU/BfN 2020; Ruddat/Sonnberger 2015). The level of support may vary between studies (probably due to different measurement approaches, i.e. question wording, item scales), however the overall picture is quite clear and stable.
Although public surveys in Germany and beyond show high degrees of approval of renewable energies, in particular compared to carbon and nuclear energy, goal conflicts are constantly articulated and debated with regard to nature protection, land use, air safety and the protection of the landscape (Devine-Wright 2007; Steentjes et al. 2017; Wolf et al. 2022; Ruddat 2022). Local siting decisions thus involve questions of distributional and procedural fairness and are frequently accompanied by local protests, court actions and sometimes high levels of media coverage (Agentur für Erneuerbare Energien 2020; Dehler-Holland et al. 2021; Wolsink 2007; Harper et al. 2019). In this context, issues of energy justice have gained increasing attention in both academic and public debates with the ongoing expansion of renewables (Jenkins et al. 2016; Bang et al. 2022; Ramasar et al. 2022). Research on energy-poor households in Germany has revealed a feeling of being excluded from the energy transition. However, this feeling does not so far appear to translate into opposition to the energy transition (Hanke et al. 2023).
Empirical research has also shown that citizens' overall willingness to pay to achieve a successful energy transition depends on a fair distribution of costs, i.e. an obligation for both (energy) industry and state actors to contribute financially (Sonnberger/Ruddat 2016). Additionally, an analysis of media reports on the German Renewable Energy Sources Act (German: EEG – Erneuerbare-Energien-Gesetz) between 2000 and 2017 shows a shift from discussions of renewable energy technologies towards discussions of the costs of the energy transition. This also entails a shift in focus from positive aspects like job creation and industry innovation towards negative aspects like the effects of the EEG on energy prices and the burden of the EEG for energy consumers (Dehler-Holland et al. 2021). Interestingly, these shifts in media attention, as well as the rising energy prices and EEG surcharges, did not have a significant influence on the general approval of renewable energies (Ruddat/Sonnberger 2015).
There is also a vast body of scientific studies from different countries all over the world concerning aspects such as the influence of cost-benefit perceptions, trust in key actors, fairness, place attachment, visual effects and environmental concerns on attitudes towards energy sources, which documents the complexity of influences on public perceptions of energy transitions (Aitken 2010; Breukers/Wolsink 2007; Haggett 2011; Jones/Eiser 2009; Sonnberger/Ruddat 2017, 2018; Swofford/Slattery 2010; Walter/Gutscher 2013; overviews in: Boudet 2019; Rand/Hoen 2017; Ruddat 2022). Thus, from a policy perspective, securing public support for energy transition policies proves to be a complex endeavor. Accordingly, Dehler-Holland et al. speak "[…] of the 'energy trilemma' policy goals of low environmental impacts, low energy costs and energy security […]" (Dehler-Holland et al. 2021: 2). In particular, environmental impacts with regard to climate change seemed to remain a somewhat psychologically distant issue for many citizens for a long time. This has changed recently. The majority of citizens

in Germany report personal experiences with extreme weather events like heat, drought and heavy rainfall. This was also the case ten years ago; however, unlike previously, respondents now also report effects on their health and fear negative future health impacts to a greater degree (BMUV/UBA 2023). Engels et al. have also shown that climate change skepticism is associated with opposition to renewables among the German population (Engels et al. 2013).

Transitions from fossil to renewable energy regimes have also become a central target of populist politics in Germany and beyond in recent years. As research has shown, populists and populist parties try to exploit opposition to renewables in order to broaden their voter base (Fraune/Knodt 2018; Radtke et al. 2019). The main arguments used by the German right-wing populist party AfD (*Alternative für Deutschland*) are that energy transitions are implemented at the expense of "ordinary citizens" and that they jeopardize economic growth and national economic competitiveness (Oswald et al. 2021). However, so far it does not seem that this narrative has been embraced by wider sections of the German population as a reason to vote for populist parties (Sommer et al. 2022). In this context, political orientation has proven to be a relevant predictor of attitudes towards transitions to renewables, with people holding more conservative views also being more skeptical (Jagers et al. 2018; Janik et al. 2021; Thomas et al. 2022).

What we can derive from this overview of the state of research are the following three points: a) general public support for the German energy transition seems to remain at a high level; b) the structures of support for and opposition to the German energy transition seem mainly to be centered around cost-benefit perceptions, fairness, political orientation and environmental awareness; and c) the focus of public debates about energy issues has changed over time. In the next section, we go into detail with regard to our empirical approach and show how we have empirically addressed the implications derived from the state of research.

2. Methods

Data

Our analysis is based on data from the GESIS Panel. The GESIS Panel is a probability-based mixed-mode panel administered by the Leibniz Institute for the Social Sciences. Comprehensive information on the set-up and implementation of the panel can be found in Bosnjak et al. (2018). The panel can be considered as representative of the population of Germany (Bosnjak et al. 2018: 112). Since the initial set-up of the panel in 2013, four to seven survey waves have been conducted each year. In our case, the data for the independent variables stem from wave a (2013) and partly also from wave b (2014), while the data for our longitudinal analysis of the dependent variable stem from the waves of each year from 2014 to 2022. Please note that the last survey wave included in our analysis was conducted between May and July 2022 – i.e. after the start of Russia's war on Ukraine in February 2022. Potential changes in attitudes towards the energy transition due to the energy crisis that unfolded with the war are thus covered by our analysis.

Statistical approach

Latent growth models

Latent growth curve (LGC) models are a popular analytical technique for examining intra-individual changes in people, the inter-individual differences in these changes, and the determinants of these processes (Grimm/Ram 2009: 124; see also: McArdle/Epstein 1987; Meredith/Tisak 1990; Preacher et al. 2008; Rogosa/Willett 1985; Urban 2004). LGC models enable the analysis of changes in a variable over time, thereby facilitating the examination of dynamic developmental processes within the framework of structural equation modeling (Urban 2004). Time-lagged repeated measurements of a variable are understood as manifest indicators of latent constructs (intercept and slope constructs), representing the initial level at the start of the survey and the change over time.

Conceptually, LGC models can be understood as a two-stage process. Initially, the individual trajectory for each analysis unit is determined (the individual growth trajectory pattern in the form of a regression equation), allowing for the establishment of an individual trajectory equation characterized by individual intercept and slope factors for each unit. In a second step, these individual trajectory equations are then summarized across all analysis units to calculate an average starting level (or baseline) and an average rate of change, each having its variance around these average values (Wickrama et al. 2016: 25). Even if this two-stage process does not correspond to the actual mathematical procedure, it illustrates the idea behind the modeling of latent constructs in the form of intercepts and slopes within the framework of LGC models. An average pattern is determined from which the analysis units only deviate to the extent that there is variance with regard to the intercept and the slope (Krause 2019).

To implement this analysis scheme within a structural equation specification, the intercept and slope factors are connected with time-lagged repeated measurements (whether implemented as manifest or latent constructs) using (partially) fixed factor loadings. These fixed factor loadings can be understood as time coefficients, defining the time axis of the growth process (Urban 2004). The form of the growth trajectory of an LGC model can take on more complex patterns than linear progression through the free estimation of individual time coefficients or the addition of polynomials in the form of extra slope factors.

The latent intercept and slope factors themselves are characterized by their respective means and variances. The means of slope and intercept represent the typical or average values of the pattern of progression of the population in LGC model logic. The degree of variation of individual analysis units with respect to this typical progression pattern is expressed through the variance of the intercept and slope factors. Additionally, the covariance between the intercept and slope factors plays a crucial role, as it reveals the relationship between initial levels and subsequent growth trajectories. A positive covariance suggests that higher starting points are associated with faster growth, while a negative covariance implies that higher initial levels may correspond to slower growth or decline. These variations in the statistical model regarding the developmental pattern of the studied variable can be statistically explained in a further modeling step through substantive dimensions (in the form of covariates) if portions of the variance of the intercept and slope constructs can be statistically explained (conditional LGC models).

However, LGC models always assume that the developmental trajectory modeled (as well as potential determinants of this trajectory) exhibits the same pattern of growth for the entire studied group, deviating only in the form of random error. LGC models thus assume that the data studied come from a single homogeneous population (with the exception of multi-group models). The respective LGC model is thus determined by an average growth trajectory pattern, defined in a latent intercept component and an average latent slope component, and the individual variation around these average constructs.

An LGC model can (and should) be specified as a second-order model, where the measurement points are not represented by manifest indicators but by latent constructs, represented by several manifest indicators (curve-of-factors form) to account for measurement error. However, with this kind of specification, it is crucial to ensure that the measurement models are equivalent across all time points. This requirement is addressed by longitudinal measurement invariance, which refers to the consistency of a measurement instrument over time, guaranteeing that the same construct is being measured in the same way across the different time points. Without establishing measurement invariance, any observed changes in the construct could be attributed to changes in the measurement instrument rather than true changes in the construct itself (Meredith/Horn 2001). Measurement invariance is assessed through a series of increasingly restrictive models, typically starting with configural invariance, which tests whether the same factor structure holds across time. Following this, metric invariance (or weak invariance) is tested by examining whether factor loadings are consistent over time. If metric invariance is established, it indicates that the relationships between observed variables and their underlying factors are stable across time points. The next step is to test for scalar invariance (or strong invariance), which involves assessing whether the intercepts of the observed variables are equivalent across time. Achieving scalar invariance is crucial because it indicates that the differences in the means of the observed variables can be attributed to changes in the latent construct, not to shifts in the measurement itself. If scalar invariance is confirmed, researchers can be confident that any observed mean differences over time reflect true changes in the underlying construct (Little 2013).

SEM Tree method

The SEM Tree method, introduced by Brandmaier et al. (2013), represents an innovative synthesis of Structural Equation Models (SEMs) and decision tree techniques. It combines the analytical strength of SEMs, which are capable of mapping complex relationships between observed and latent variables, with the ability of decision trees to divide datasets into more homogeneous subgroups. This method enables researchers to identify and quantify latent heterogeneity within data, which often remains hidden in conventional (linear) analysis methods. The SEM Tree method employs a non-parametric, data-driven approach to identify key covariates, enabling the discovery of nonlinear, interactive and non-monotonic effects without requiring prior specification of these effects (Brandmaier/Jacobucci 2023). This approach contrasts with similar modeling methods, such as mixture models, which also identify latent groups/heterogeneity in a data-driven manner but do not do so with respect to the predictors of latent class membership. Instead, mixture models typically apply parametric effects for the predictors, requiring prior specification by the researcher. As a result, the SEM Tree method leans more towards an exploratory, data-driven approach rather than a confirmatory one in terms of covariate effects.

A key aspect of the SEM Tree method is its ability to recursively divide data into subgroups by searching for covariates that lead to significant differences in SEM parameter values. This approach is particularly advantageous for uncovering hidden patterns and relationship structures in social science data that are not apparent due to sample heterogeneity. Jacobucci et al. (2017) emphasize that this method allows the identification of subgroups that respond differently to certain predictors or conditions, leading to more precise model specification and more accurate, meaningful results. SEM Trees also provide an exploratory means of investigating complex data structures, especially in areas such as attitude research or longitudinal analysis.

The SEM Tree method typically begins with the definition of a base model within the SEM framework that describes the relationships between observed variables and latent constructs. The SEM Tree algorithm then examines the dataset to find covariates that cause significant heterogeneity in SEM parameter values. By recursively dividing the dataset at points where the differences in the parameters of the base model are maximized, the data are divided into smaller, more homogeneous subgroups. This process continues until no significant improvement of the model can be achieved or other termination criteria are met (e.g. a minimum number of observations in a (sub)model or a user-specified maximum number of splits).

With each division, statistical tests such as likelihood ratio (or Lagrange Multiplier Tests) are conducted to assess the significance of the differences between subgroups. The final tree structure is then evaluated for its statistical quality and practicability, using methods such as cross-validation or information criteria (e.g. AIC, BIC) to assess model fit and avoid overfitting.

In the analysis of growth curve models, the SEM Tree method offers an innovative perspective for examining individual developmental trajectories and proves to be an advanced tool that helps to unravel the complexity of longitudinal data patterns. It provides new insights that might not be attainable with traditional methods. Its ability to uncover latent patterns and heterogeneities in data through non-parametric effects makes it an interesting approach within the research toolkit. Taken together, the application of SEM Trees to growth curve models enables detailed, nuanced and more assumption-free analysis of developmental trajectories, contributing significantly to the understanding of developmental processes.

However, while it is true that the SEM Tree method offers advantages in detecting latent heterogeneity within data, it also comes with several limitations that need to be considered. One of the primary challenges of SEM Trees is their reliance on a recursive partitioning algorithm that can be overly “greedy” because of its local optimization criterion which does not take into account all following splits. This means that each split made by the SEM Tree is conditional on previous splits, leading to a path-dependent model structure. Consequently, an incorrect or suboptimal initial split can significantly affect all subsequent divisions, potentially resulting in a less accurate representation of the underlying data structure (Brandmaier et al. 2016).

Additionally, SEM Trees can result in overfitting, especially when the algorithm is allowed to grow very deep trees without sufficient control measures. As SEM Trees perform an exhaustive search for optimal splits, they are prone to identifying patterns that may not generalize well to new samples, particularly when the sample size is small or the model is very complex. The risk of overfitting necessitates careful consideration of stopping criteria and model evaluation methods, such as cross-validation or pruning techniques, to ensure the model’s robustness and generalizability (Brandmaier et al. 2013).

SEM Forests, like traditional random forest models, are a natural extension of SEM Tree models. They aggregate multiple SEM Trees to enhance estimation stability and predictive accuracy, especially in high-dimensional and complex datasets. By averaging across a forest of SEM Trees with bootstrapping/subsampling of cases and randomization of the considered covariates for the splits, this approach mitigates the risk of overfitting associated with single-tree methods and provides a more robust understanding of underlying data patterns (Brandmaier et al. 2016). This ensemble strategy increases the reliability of results and can improve the detection of subtle covariate effects that might be missed by a single SEM Tree.

However, despite these advantages, SEM Forests present significant challenges, particularly concerning interpretability and computational demands. While a single SEM Tree provides a clear, interpretable model structure that shows exactly how covariates influence the division of data into subgroups, SEM Forests, which rely on a collection of numerous trees, make it more difficult to interpret the specific influence of individual covariates on model outcomes. The aggregation process, while increasing stability, also obscures the simplicity and transparency that single-tree models offer. As a result, while SEM Forests can reveal more complex relationships, the clarity of those relationships is often diminished compared to the direct, visual representation provided by a single SEM Tree. Moreover, the computational burden of SEM Forests is substantially higher than that of single SEM Tree models. As each tree in the forest must estimate a complete SEM model multiple times, the computational time and resources required can increase dramatically, especially when dealing with large datasets or complex SEMs involving numerous latent variables and paths. This increased computational demand may make SEM Forests less feasible for researchers with limited time or computational resources (Brandmaier et al. 2016; Jacobucci et al. 2017). Thus, while SEM Forests offer enhanced estimation stability and robustness, their use comes at the cost of reduced interpretability and increased computational complexity.

Logic and procedure of SEM Trees for latent growth models

This method, which allows for a detailed analysis of growth data, is computationally intensive as a new model must be estimated for each potential division (especially for metric covariates). However, it allows a comprehensive examination of growth patterns in different subgroups, thus enabling a deeper understanding of growth dynamics (Usami et al. 2019). Nominal data can also be included as covariates, with the dataset being divided according to membership in specific categories.

The application of the SEM Tree method to growth curve models (growth models) in our case can be summarized, following Usami et al. (2019), as follows:

Adaptation of the base model to growth data: A latent growth curve model (LGCM) is applied as the base model to the complete set of growth data. This model includes key growth parameters such as intercept, slope and their covariance. The fit of the model to the data is determined through likelihood calculation.

Identification of covariates for data division and evaluation: The next step in the SEM Tree algorithm involves searching the dataset for a covariate that produces the greatest differences in the (growth) model parameters (e.g. variance and covariance of intercept and slope with corresponding means) between different subgroups. If not otherwise specified, the residual variances can also contribute to fit differences.[1] The dataset is accordingly divided into two subgroups (A and B) where, in case of metric or ordinal covariates, one group meets the condition that the covariate exceeds a certain value (M ≥ m) and the other falls below it (M < m). Nominal covariates can also be included as covariates in SEM Trees (e.g. Brandmaier et al. 2013). In this case, data are split on the basis of whether a participant belongs to a specific set A or its complement set B (all other categories). A test is conducted to determine if dividing the dataset into these subgroups leads to a significant improvement in the model. This is classically assessed using a chi-square test, which measures the change in model fit before and after the division. In the application of Structural Equation Model (SEM) Trees, researchers have two central methodological approaches at their disposal: the Naive Test and the Score Test (Arnold et al. 2021). These methods serve to decide whether and how a dataset should be divided into subgroups to better capture the heterogeneity of the population. The Naive Test is based on the principle of the Likelihood Ratio Test. This approach assesses the necessity of splitting the dataset by comparing the model fit before and after the potential division. Specifically, it examines whether dividing the dataset based on an observed covariate leads to a significantly different model fit. However, this process is computationally intensive, as a new model must be estimated for each potential splitting point in the dataset. By contrast, the Score Test, also referred to as the Lagrange Multiplier Test, employs a more subtle approach. Instead of directly modeling each potential splitting scenario, this test examines case-wise derivatives of the likelihood function for systematic patterns and thus provides a computationally efficient alternative to the maximum likelihood test. This method aims to identify indicators of heterogeneity in the data without having to recalculate the model for every possible division. The advantage of the Score Test lies in its efficiency and lower computational intensity, making it particularly useful for extensive datasets or complex models.

Repetition of the process in subgroups: If significant improvement is observed through the partitioning, the process is repeated in each newly formed subgroup until no further improvement is achieved. The final number of remaining subgroups represents the estimated number of growth classes in the SEM Tree.

Measures and data handling

In our analysis, we have employed a two-step analytical strategy to explore the dynamics of attitudinal changes towards the energy transition in Germany. Our first step involved estimating a classic conditional growth curve model (CGCM). This model allowed us to analyze changes in attitudes over time and understand both intra-individual changes and inter-individual differences. We focused on key latent constructs, namely the intercept and slope, representing the initial level of attitudes at the start of the survey and their change over time.

The CGCM can reveal relevant findings about the influences of various factors (covariates) on the trajectory of attitudes in a linear way. Building upon the CGCM, we employed the SEM Tree method to achieve a more detailed analysis of the growth pattern by analyzing the non-parametric effects of the covariates. This innovative approach, combining Structural Equation Models (SEMs) and decision tree techniques, enabled us to identify latent heterogeneity within the data, which often remains obscured in conventional linear analyses. The SEM Tree method's recursive partitioning can help us discover significant differences in SEM parameter values across subgroups, unveiling hidden patterns and relationship structures. By integrating and comparing the CGCM and SEM Trees in our analysis, we can achieve a nuanced understanding of the development of attitudes towards the energy transition. This combination of methods provides a comprehensive explorative view, not only capturing the average trajectory of attitudes but also uncovering subgroup-specific patterns.

1 We therefore use "focus parameters" that only consider differences with respect to a subset of growth parameters (see section 4.2).

In a first step, we constructed measurement models (CFAs) for attitudes towards the energy transition in the first wave of the panel data (see Table 1 for the manifest indicators) and for the New Ecological Paradigm scale (NEP scale) based on the cross-sectional data. We achieved a very good fit to the empirical data, with good to acceptable factor loadings. The scale measuring attitudes towards the energy transition exhibits a Cronbach's alpha of 0.78, indicating good internal consistency, with McDonald's omega at 0.79, further reinforcing reliability. The one-factor model was identified using the marker variable approach, demonstrating a good fit with CFI of 0.95, SRMR of 0.04 and RMSEA of 0.08. The descriptive characteristics of the items used for operationalizing the attitude towards the energy transition can be found in Table 7 in the appendix.

The NEP scale developed by Riley Dunlap and Kent van Liere to measure environmental awareness has been widely used internationally (original version of the scale: Dunlap/van Liere 1978; revised version of the scale: Dunlap et al. 2000). The NEP scale is not an attitude scale in the narrower sense, as it does not take into account the affective and conative dimensions of attitudes, i.e. those relating to intentions to act (Best 2011: 243). According to Dunlap et al. (Dunlap et al. 2000), the NEP scale is intended to depict an ecological worldview. The items on the NEP scale therefore have a high degree of abstraction. Both Paul Stern and Thomas Dietz (Stern & Dietz 1994) and Henning Best and Jochen Mayerl (Best/Mayerl 2013) locate the NEP scale in a hierarchy of mental constructs as a mediator between abstract values (e.g. post/material value orientations) and specific environmental attitudes. The NEP scale can thus be understood on a theoretical level as an antecedent of the more specific attitude towards the energy transition as a dependent variable. The descriptive characteristics of the items included in the NEP scale can be found in Table 6 in the appendix. Please also see Table 6 in the appendix for a comprehensive overview of all the characteristics of all further independent variables included in the analysis: gender, household net income, households with children under 16, household social class perception, left-right scale, political interest, residence categorization, age, citizenship, highest educational degree and household size.

We conducted a longitudinal measurement invariance analysis focusing on both the factor loadings (metric invariance) and the intercepts (scalar invariance) of the manifest variables for the construct "Attitudes towards the energy transition," using the marker variable approach for the item "All energy-saving measures are ultimately exaggerated." The examination of ΔCFI and ΔRMSEA values revealed no significant deterioration in model fit across

Selected item formulation (translated)	Variable code of the item in waves b to j
All energy-saving measures are ultimately exaggerated.	bczd029a, cczd026a, dczd026a, eczd026a, fczd026a, gczd026a, hczd025a, ibzd025a, jbzd025a
The energy transition is destroying Germany's industrial base.	bczd031a, cczd028a, dczd028a, eczd028a fczd028a, gczd028a, hczd027a, ibzd027a, jbzd027a
The future lies in renewable energies. (recoded)	bczd028a, cczd025a, dczd025a, eczd025a, fczd025a, gczd025a, hczd024a, ibzd024a, jbzd024a
The so-called "energy transition" does moreharm than good.	bczd024a, cczd021a, dczd021a, eczd021a, fczd021a, gczd021a, hczd020a, ibzd020a, jbzd020a
Renewable energies are simply not sufficient to supply an industrial country.	bczd023a, cczd020a, dczd020a, eczd020a, fczd020a, gczd020a, hczd019a, ibzd019a, jbzd019a
There is no alternative to switching to renewable energies. (recoded)	bczd032a, cczd029a, dczd029a, eczd029a, fczd029a, gczd029a, hczd028a, ibzd028a, jbzd028a

Table 1: Operationalization of the dependent latent construct: attitude towards the energy transition

these analyses, with delta values under 0.01 (Cheung/Rensvold 2002; Rutkowski/Svetina 2014). Consequently, we can conclude that scalar invariance (or strong invariance) holds over time for this construct, meaning that observed mean differences over time reflect true changes in the underlying construct (Little 2013) (see appendix Table 4).

As the next step in the analysis, we specified an unconditional non-linear growth curve model for attitudes towards the energy transition with scalar invariance (see Figure 1) with the lavaan package in R (Rosseel 2012). We utilized a freely estimated loadings growth model (Bollen/Curran 2006) to estimate a nonlinear growth curve with only two latent growth factors. We fixed the first loading of the slope factor at the value "1" and the last loading at the value "8," which sets the scale of the slope variable to "change per year" (because data were annual measurements), and estimated the remaining loadings freely. The free-loading growth model was employed due to its ability to capture non-linear changes over time more flexibly than linear or quadratic models, allowing for a more nuanced understanding of potential non-linear patterns in longitudinal development. We achieved a very good fit to the empirical data. The growth model with invariant factor loadings and intercepts achieved a good fit, with a CFI of 0.964 (scaled: 0.966), TLI of 0.960 (scaled: 0.960), RMSEA of 0.025 (scaled: 0.021) and SRMR of 0.040, all indicating a close enough match between the model and the data. The basic structure of the model can be found in Figure 1, and the factor loadings of the model can be found in Table 5 in the appendix. Figure 2 illustrates the growth trajectories estimated by the model for all fully observed cases, along with the averaged overall trajectory.

For the initial CFA analyses and the unconditional and conditional growth curve models, the full information maximum likelihood (FIML) estimation method was used for the missing treatment due to its comparatively good performance (Wahl 2020). For the SEM Tree models, only the covariates were imputed using the missForest package (Stekhoven/Bühlmann 2012), whereas a listwise deletion was used for the dependent construct in order not to distort the results and since no more elaborate missing treatment is available on the software side.

3. Results

Results: CGCM

To answer our analytical empirical question on the determinants of the development of attitudes towards the energy transition, we first interpret the conditional growth curve model, which takes into account the determinants we have examined as linear regressors of the latent growth factors. The achieved model fit was also satisfactory for this model.

The chi-square test statistic of 5886.914 with 1862 degrees of freedom and a p-value of 0.000 suggests that the model does not perfectly fit the data. However, the significance of this test can be sensitive to large sample sizes. Both Comparative Fit Index (CFI/CFI_scaled: 0.957/0.958) and Tucker-Lewis Index (TLI/TLI_scaled: 0.952/0.954) values are above 0.95, indicating a good fit of the model to the data. These indices compare the user model to the baseline model, with values closer to 1.0 suggesting a better fit. The RMSEA of 0.017 (scaled: 0.015) and its 90% confidence interval suggest a close enough fit of the model to the data. RMSEA values below 0.05 generally indicate a good fit. An SRMR value of 0.037 is also acceptable, further indicating a good model fit. In sum, the model demonstrates a good fit to the data with high CFI and TLI values and low RMSEA and SRMR values, despite the chi-square test's indication of an imperfect fit, which is influenced by the large sample size.

Our analysis of the regressors in the conditional growth curve model highlights the impact of various factors on the trajectory of attitudes toward the energy transition in Germany over time. For the intercept, the strongest predictor is the NEP score, indicating that this score is a crucial determinant of individuals' initial attitudes.[2] While

2 The NEP score was coded such that high values indicate disagreement with a "pro-ecological" worldview, while low values represent agreement.

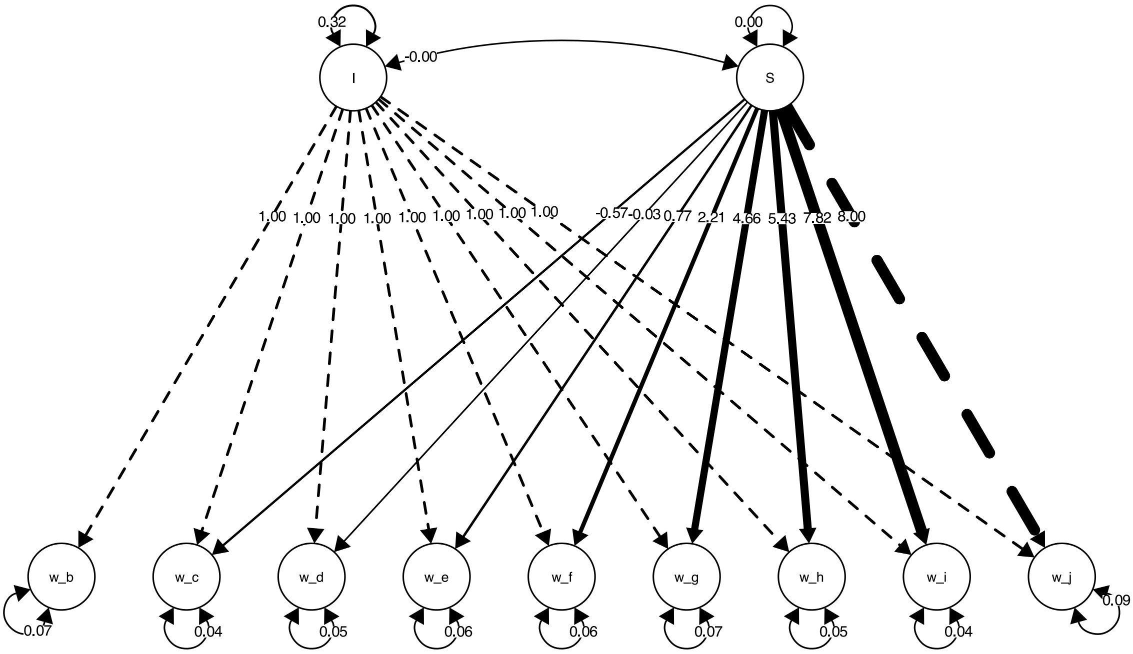

Figure 1: Unconditional non-linear latent growth curve model with free-loading growth factor coding (figure without manifest indicators, mean structure and error correlations to enhance clarity and readability; dashed paths were fixed, while solid lines represent free estimates).

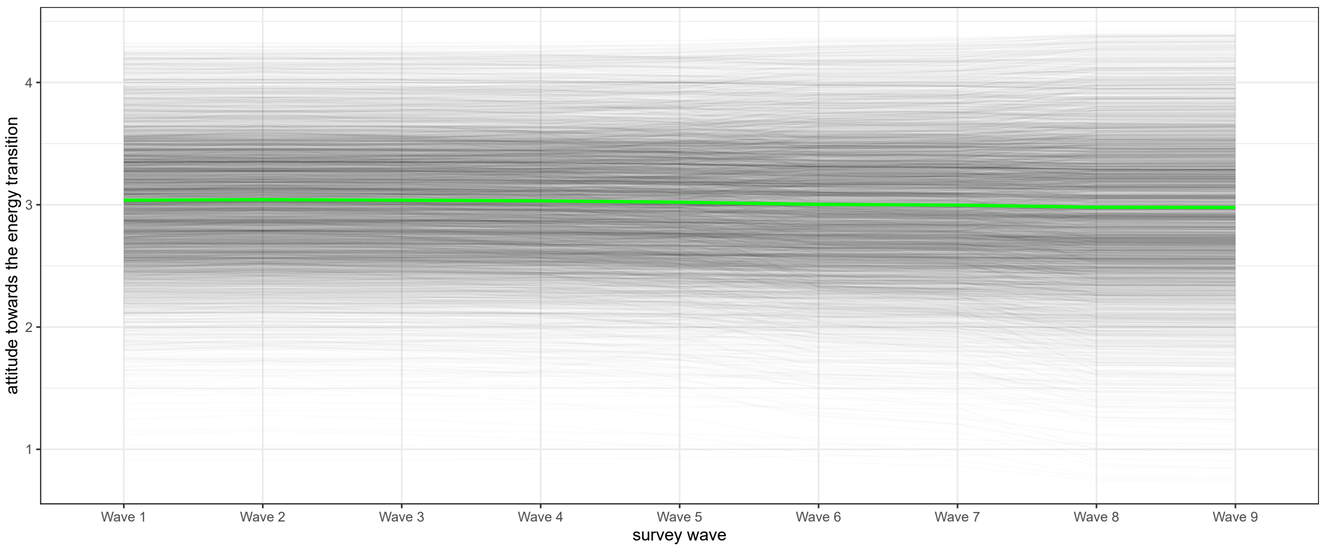

Figure 2: Growth trajectories estimated according to the unconditional non-linear latent growth curve model with free-loading growth factor coding.

other variables such as political interest, position on the left-right political spectrum, education, household income and perceived social class also exert influence, their effects are comparatively less pronounced.

However, the slope – representing the rate of change over time – is influenced in a different manner. Gender – specifically being male – emerges as the most significant factor, suggesting that gender differences play a more substantial role in the dynamics of change over time than in initial attitudes, where the effect was small and non-significant. The NEP score and position on the left-right scale also impact the slope, with a higher NEP score and a more left-leaning political orientation associated with positive growth over time. Other factors, such as political interest and German citizenship, appear to have minimal influence on the rate of change. Notably, a pro-ecological worldview (NEP) is associated with slower growth or even a decline in support for the energy transition. While a pro-ecological worldview increases the intercept, thereby raising the initial level of support for the energy transition, it negatively influences the change over time, as reflected in the slope. In contrast, factors such as perceived social class and education level positively influence the intercept but have only a moderate impact on the change dynamics, as reflected in the slope. The overall explained variance (R-squared) for the intercept (0.29) and the slope (0.061) suggests that while these factors collectively account for a moderate amount of variance in the intercept, their influence on the slope is relatively limited.

Results: SEM Tree method

In our SEM Tree analysis, we utilized the "semtree" package in R (Brandmaier et al. 2023) with specific parameters to optimize the model's performance and prevent overfitting. The focus parameters – specifically the (co-) variances and mean values of the intercept and slope – and the free loadings of the slope factor serve as key indicators in the SEM Tree analysis, capturing the central tendencies and variability within the identified subgroups, and thus providing insight into the underlying structure of the data. In the context of the SEM Tree package, focus parameters refer to the specific model parameters of interest that are examined across the different subgroups within the tree. These parameters are the focus of the recursive partitioning process, which seeks to identify how subgroups differ with respect to these key characteristics, thereby revealing the latent structure and heterogeneity in the data. When focus parameters are specified, SEM Trees will evaluate heterogeneity

Regressors	Intercept			Slope		
	Std. coeff	Coeff.	SE	Std. coeff	Coeff.	SE
NEP score	-0.285	-1.329	0.107	0.113	0.049	0.017
Gender (male=1)	0.011	0.012	0.018	-0.162	-0.017	0.003
Household net income	0.103	0.019	0.004	-0.018	0.000	0.001
Households with children under 16	0.064	0.073	0.025	-0.011	-0.001	0.004
Household social class perception	0.106	0.073	0.011	0.065	0.004	0.002
Political interest	0.183	0.118	0.011	0.002	0.000	0.002
Residence categorization	0.022	0.012	0.009	0.040	0.002	0.001
Age	-0.028	-0.001	0.001	-0.070	0.000	0.000
German citizenship	0.058	0.125	0.041	0.032	0.006	0.008
Highest educational degree	0.145	0.096	0.012	0.051	0.003	0.002
Left-right scale	-0.181	-0.052	0.005	-0.090	-0.002	0.001
Household size	-0.020	-0.009	0.011	0.016	0.001	0.002
Sum of explained variance (R-squared)			0.290			0.061

Table 2: Linear regressors of the conditional growth curve model
Note: n = 4.248 with FIML estimation as missing method

exclusively within these parameters, disregarding any group differences in the other parameters when determining a split (Arnold et al. 2021).
In addition to using focus parameters for uncovering the heterogeneity of a subset of the model parameters, we specified not only the temporal invariance in the LGCM but also the global invariance of these parameters (factor loadings and intercepts) across the estimated groups within the tree. This ensures that differences in the growth parameters can be attributed to actual differences in the growth trajectory shapes rather than merely to measurement differences between the identified subgroups.
In our analysis, the minimum number of cases in each node was set to 150. This threshold ensures that each leaf node has a sufficient number of cases for a reliable SEM estimation, avoiding the risk of models that are too specific to small sample idiosyncrasies and therefore not generalizable. We are guided by the minimum sample size recommendations of Curran et al. (2010) and L.K. Muthén/B.O. Muthén (2002) and the complexity of our second-order LGCM. We would have liked to have opted for the "score" method over the "naive" method, because the score method represents computational efficiency, which is particularly important given the complexity of our models, and additionally has better statistical properties (Arnold et al. 2021). The score method is adept at detecting heterogeneity in SEM parameters without the need for computationally intensive recalculations for every potential split. However, a software limitation in the "semtree" package necessitated the use of the naive method.[3] Additionally, we employed a Bernoulli correction to address the multiple comparisons issue,thereby further reducing the risk of overfitting. This correction ensures that our model remains robust and avoids false discoveries that could arise from testing numerous hypotheses. To streamline the calculation related to the decision tree, we reduced the metric variables NEP and age into 10 equal-sized groups. This approach minimizes the number of splits to be examined while retaining most of the information regarding the covariates.
Figure 3 depicts the structure of the estimated SEM Tree. The splits are clearly dominated by the NEP score covariate. Nodes/Leaves 4, 5, 7, 8, 10, 12 and 13 represent these final groups, containing specific case numbers indicating the size of the respective subgroups. The tree structure elucidates how the data are segmented into different subgroups based on NEP scores, which act as the main splitting variable here, with additional splits based on education, household net income and political orientation. At the root of the tree (Node 1), the entire sample is bifurcated into two groups according to a threshold value of the NEP score. Those with an NEP score above this threshold follow the right branch of the tree, while those below follow the left branch. This initial split suggests that the NEP score is a significant predictor for grouping attitudes toward the energy transition. On the next level, Nodes 2 and 9 further divide the groups based on the highest educational level and household income, indicating a nuanced differentiation within this subgroup. In the following, the final groups are briefly characterized:

- Leaf 4: Lower level of education + very strong ecological worldview
- Leaf 5: Lower level of education + strong ecological worldview
- Leaf 7: Higher level of education + somewhat left-leaning political orientation + strong ecological worldview
- Leaf 8: Higher level of education + somewhat conservative political orientation + strong ecological worldview
- Leaf 10: Lower household income + weak ecological worldview
- Leaf 12: Higher household income + weak ecological worldview
- Leaf 13: Higher household income + very weak ecological worldview

Table 3 provides a detailed overview of the estimates within the leaves of a Structural Equation Model (SEM) Tree, presenting various statistical measures for each leaf, including the number of cases, variances, covariances and

3 It was not possible to set global invariant parameter estimates in the 0.9.20 version of the package "semtree" while using the score method.

mean values for the intercept and slope, and also the freely estimated growth factor loadings which allow for different trajectories within the groups. Figure 4 depicts the mean estimated trajectory of the groups which result from the values of Table 3 and shows the general trend within the subgroups of the tree.
The number of cases in each leaf of the SEM Tree shows some variation, ranging from as few as 153 in one leaf to as many as 278 in another.

The variance of the intercept across different leaves varies, with the highest being 0.381 and the lowest 0.146. Higher variance values indicate a wider spread of the intercept within that subgroup, suggesting more variability in the starting point of the growth trajectory. The covariance between the intercept and slope across the leaves is relatively low, which suggests a weak relationship between the intercept and slope values within the leaves. Regarding the variance of the slope, the values are generally small (between 0.001 and 0.004), indicating that the rate of change represented by the slope is relatively consistent within the groups.
The Structural Equation Model (SEM) Tree analysis reveals notable patterns in the mean slope and intercept parameters across various groups. Notably, the mean slope values are relatively low and exhibit minimal variation between groups. However, a closer examination reveals that some groups demonstrate a general positive growth trend, while others show a negative growth pattern over time. These trends can be best seen in the trajectories of Figure 4 because they incorporate the slope means with the free factor loadings of the slope. Groups 4 (lower education + very strong ecological worldview), 12 (higher household income + weak ecological worldview) and 13 (higher household income + very weak ecological worldview) in particular show a decreasing approval of the energy transition over time. Groups 7 (higher level of education + somewhat left-leaning political orientation + strong ecological worldview) and 8 (higher level of education + somewhat conservative po-

Cases	191	278	226	243	269	153	221
No. of leaf/group	4	5	7	8	10	12	13
Variance intercept	0.277	0.159	0.185	0.241	0.146	0.166	0.381
Variance slope	0.001	0.002	0.001	0.002	0.002	0.004	0.002
Covariance intercept-slope	0.003	-0.001	-0.001	-0.007	-0.002	0.001	-0.003
Mean intercept	3.032	3.198	3.521	3.128	2.622	3.058	2.809
Mean slope	-0.012	-0.009	0.007	0.013	-0.010	-0.028	-0.017
Fixed FL wave b	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Free FL wave c	-1.779	-0.148	0.383	0.932	0.293	-1.572	-0.154
Free FL wave d	0.411	0.001	-1.808	1.599	0.993	-0.298	-1.114
Free FL wave e	-1.198	1.384	1.099	3.479	1.792	-1.908	-0.734
Free FL wave f	0.443	2.517	3.531	5.242	1.868	-0.058	3.144
Free FL wave g	5.740	4.599	4.594	6.265	4.391	3.913	4.809
Free FL wave h	4.731	4.952	7.057	7.443	6.391	4.033	5.574
Free FL wave i	9.660	7.909	7.756	7.656	8.810	6.213	7.963
Fixed FL wave j	8.000	8.000	8.000	8.000	8.000	8.000	8.000

Table 3: Estimates in the SEM Tree leaves
Note: n=1581 (since only listwise case exclusion is available in SEM Trees); FL = factor loading of the slope factor

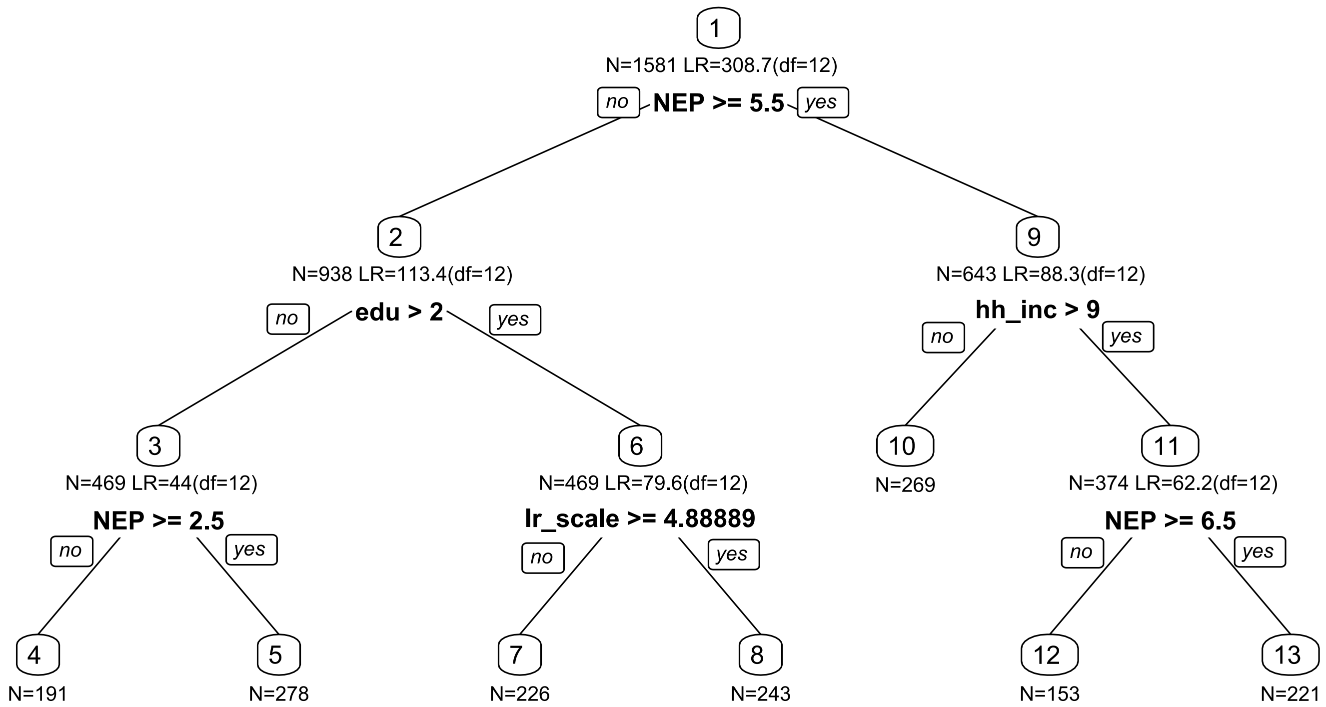

Figure 3: SEM Tree structure

Note: lr_scale = left-right scale, hh_inc = household net income, edu = highest educational degree

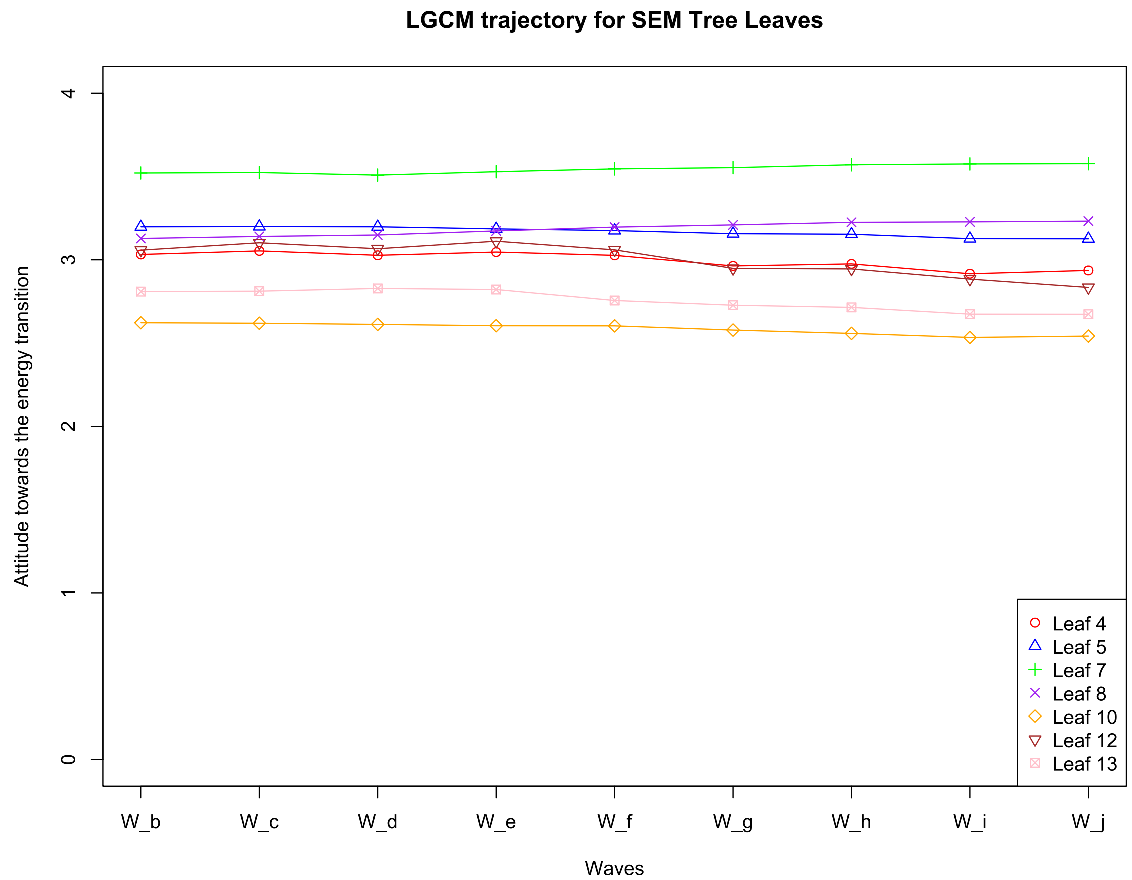

Figure 4: Mean trajectories of the leaves in the SEM Tree model

litical orientation + strong ecological worldview), on the other hand, tend to show an increase in approval. Despite this difference over time, the absolute level of approval for the energy transition remains comparatively constant and inter-individual differences mainly manifest through the intercept values. In general, the highest approval rate is found in Group 7 (higher level of education + somewhat left-leaning political orientation + strong ecological worldview) and the lowest in Group 10 (lower household income + weak ecological worldview).

In contrast to the slope means, which show minimal variation, the mean intercept values exhibit more pronounced differences between groups. These discrepancies in intercept means suggest that the starting points or baseline levels vary significantly across groups. This pattern indicates that different subgroups may have distinct initial levels of approval, but follow relatively parallel trajectories over time, with small deviations between the groups. This observed pattern, characterized by low slope means coupled with variable intercept means, is indicative of scenarios where different subgroups start from disparate baselines but exhibit similar developmental or change patterns over time.

When we combine the observations that the splits are dominated by the NEP covariate and that the main difference between the leaves (meaning: groups) of the SEM Tree are found in the mean intercept value, then we see that the results of the conditional growth model are to some degree replicated with the more advanced SEM Tree method.

In summary, our findings present a comprehensive picture of attitudes toward the energy transition over time. The analysis suggests that these attitudes are notably stable and exhibit minimal but differentiated change. The primary variation observed is in the intercept of attitudes among individuals. Regarding the determinants examined, the NEP score emerges as the most influential factor, but it primarily affects the baseline level, or the intercept, of these attitudes. This pattern is evident in both the conditional growth curve model and the SEM Tree model. Thus, in essence, attitudes towards the energy transition are remarkably stable and are mainly influenced by the NEP score.

4. Discussion

Drawing on longitudinal data from the GESIS Panel, we have exploratively examined the question of whether it is possible to identify social groups with distinct characteristics that systematically vary with regard to their attitude towards the German energy transition. Additionally, we have asked whether public opinion towards the German energy transition varies over time (2013 to July 2022) and if so, whether there is variation in the attitudes towards the German energy transition among specific social groups. Our analysis approach is characterized by a fairly novel application of Structural Equation Model (SEM) Trees based on a latent growth curve model (LGCM) and conventional conditional latent growth curve models. This approach allowed us to inductively identify subgroups with different growth trajectories based on covariates and compare these results between the different analysis techniques. In a nutshell, we found that of the variables included in the conditional model, the NEP score (i.e. ecological worldview), education, the left-right scale (i.e. political orientation) and political interest are the most relevant predictors of attitudes towards the energy transition at the beginning of our data time series. An ecological worldview, a high educational level, a left-leaning political orientation and a high level of political interest are thus associated with a high rate of approval of the energy transition. Furthermore, our analysis shows that attitudes towards the energy transition are notably stable over time and exhibit minimal change. The SEM Tree approach reveals that the NEP score in particular, but also education, political orientation (left-right) and household net income are relevant variables for identifying subgroups with distinct perception profiles with regard to the energy transition. The SEM Tree model also showed that group differences are primarily located in the initial level of attitude and that this attitude does not change significantly over time, which mirrors the results from the conventional conditional model.

More specifically, our analyses yielded seven subgroups with distinct attitudes towards the German energy transition. The main factor dividing these groups is the NEP score of the respective individuals. However, education, political orientation (left-right) and household net income are also of relevance for grouping individuals. In our study, an ecological worldview is the main factor influencing the attitude towards the energy transition. This suggests that attitudes towards the energy transition are mainly derived from a more cognitively abstract ecological worldview. This is in line with the findings of Best and Mayerl (2013), which indicate that ecological worldviews measured by the NEP scale influence more specific environmental attitudes. Income has also previously been reported to have a positive influence on the perception of environmental issues and renewable energies. For example, it is positively correlated with acceptance of offshore and onshore wind energy as well as awareness of biodiversity (BMU/BfN 2020). Our results are in line with these previous findings. The positive correlation between income and approval of renewable energies – even when controlled for education – may potentially stem from lower levels of fear regarding costly environmental regulations among more affluent households. This may indicate a kind of "environmentalism of the rich" (Dauvergne 2018). We also observed that the group with the lowest approval of the energy transition (Group 10) is characterized, among other things, by a comparatively low household net income. This also suggests that issues of social inequality affect people's perception of the energy transition. It therefore comes as no surprise that political debates around energy policies – such as the Buildings Energy Act (German: GEG – Gebäudeenergiegesetz) in summer 2022 – are also accompanied by argumentation concerning the fear of deepening social inequalities through energy policies. All of this suggests that energy policies should be accompanied by respective social policies in order to avoid issues of social injustice. We also found that a higher level of education is associated with approval of the energy transition. This is in line with previous studies on renewables and ecological issues. For example, quantitative studies from Germany report positive correlations between higher educational levels and willingness to engage in local nature protection measures, awareness of biological diversity, acceptance of wind and solar energy and environmental awareness in general (BMU/BfN 2020; Liebe/Dobers 2019; UBA 2021). The fact that attitudes towards the energy transition are relatively stable over time corresponds with the overall finding of consistent support for the German energy transition in other longitudinal surveys (see e.g. BMU/BfN 2020; Ruddat/Sonnberger 2015).

According to our findings, the public debates concerning energy prices following the beginning of the war in Ukraine do not seem to have had a negative influence on the general level of support (at least within the timeframe of our data). This is interesting given that the transformation of the energy system is widely framed as costly (at least in the beginning) and that energy prices could rise with the further implementation of the transition. It also supports the view that the majority of citizens in Germany might see renewable energies as one way to become more independent from external energy sources, which has become an important factor in the context of the energy crisis. Additionally, ecological worldviews as measured by the NEP scale seem to be a main factor in people's approval of the energy transition. Together with the fact that individuals with a more left-leaning political orientation tend to approve of the energy transition, this can be seen to reflect a stable left-green value basis for the transformation project.

Overall, the attitude towards the energy transition among the identified subgroups is also remarkably stable over time. This suggests that there are no signs of an intensifying polarization between different parts of the German population with regard to the energy transition within the timeframe observed (2013 to July 2022). However, this could change in the future when questions of social justice might become more strongly associated with energy policies, such as in the case of the Buildings Energy Act. Intensified public debate around climate change triggered, among other factors, by the emergence of the Fridays for Future movement and the reforms of the Renewable Energy Sources Act (EEG) and associated political debates also seem to have had no notable impact on attitudes towards the energy transition in the different identified subgroups.

5.Conclusion

All in all, according to our analyses, support for the energy transition is quantitative (overall approval rate among the German public and in specific social subgroups) as well as qualitative (value basis). This could have relevant implications for policy decisions, as there have been extensive and controversial public debates about new legislation in the energy sector since the beginning of the war in Ukraine. A prominent example was the fierce controversy over the above-mentioned Buildings Energy Act with regard to heat pumps in private houses. Such controversies show that a general approval of the transition to renewables may quickly vanish when plans are made to implement concrete decarbonization measures that are perceived as socially unjust. The goal of decarbonization may be set and more or less universally supported, but the way ahead still remains unclear. Controversies will continue to arise in the future, in particular when concrete policy measures create goal conflicts. The main goal conflict – as reflected in the controversy around the Renewable Energy Sources Act – exists between a rapid decarbonization on the one hand and social equity and sustainable welfare on the other (Bohnenberger 2023). Decision-makers should therefore aim to design a roadmap for achieving the designated target which takes into account the personal living conditions and available financial resources of citizens, as well as issues of social justice. Developing ideas, programs and institutions for sustainable welfare in order to ensure that sustainability transformations are implemented in a socially just way seems to be a crucial task here.

Advances in statistical methods have equipped social researchers with more advanced means of analyzing longitudinal data in more detail. In the face of ecological crises, there is a need for a better understanding of the long-term development of the public perceptions of socio-ecological transformation processes, in order to be able to explain how support for and opposition to transformation processes is brought about over time. In particular, as transformation projects such as the energy transition progress, their social implications will become more and more evident – and in a potentially controversial way. Here, sociology with its conceptual and methodical tools for understanding the causes and dynamics of social inequalities has a lot to contribute.

Another avenue for future research is unpacking how goal conflicts in the context of the energy transition are perceived by citizens and what can be done to overcome such goal conflicts. It is clear that while policies benefit some, others are worse off as a result. Also, what is effective from an ecological perspective may be problematic from a social perspective. Finding ways to navigate such goal conflicts and balance social and ecological needs – while keeping in mind that goal conflicts can never be fully resolved – appears to be a central issue when it comes to securing public support for energy transition policies. In this context, developing a deeper empirical and conceptual understanding of the interplay between an abstract approval of socio-ecological transformation processes and the conflicts and oppositions which emerge at the level of concrete projects and policies is also important. Despite being criticized for more than 20 years now, the concept of NIMBYism still looms large in public debates and among policy-makers (Wolsink 2000; Carley et al. 2020). While the social sciences have developed a sophisticated and nuanced theoretical understanding of opposition towards energy projects and policies (Ellis et al. 2023), a comprehensive theoretical basis for analyzing socio-ecological transformations in the sense of cross-sectoral reconfigurations of society-nature relations and their associated societal dynamics is still lacking.

Acknowledgements

We would like to express our gratitude to Eleri Luff for the invaluable assistance with language editing and to Lukas Günsch for the support with the formatting of the paper. Furthermore, we would like to thank the two anonymous reviewers whose constructive comments and feedback were extremely helpful in improving the quality of our paper.

Disclosure Statement

We have no conflicting interests to declare.

References

Agentur für Erneuerbare Energien (2020): Akzeptanz in der Fläche, Protest im Lokalen?

Aitken, M. (2010): Wind power and community benefits: Challenges and opportunities. In: Energy Policy, 38(10), pp. 6066–6075.

Arnold, M./Voelkle, M. C./Brandmaier, A. M. (2021): Score-Guided Structural Equation Model Trees. In: Frontiers in psychology, 11, 564403.

Bang, G./Rosendahl, K. E./Böhringer, C. (2022): Balancing cost and justice concerns in the energy transition: comparing coal phase-out policies in Germany and the UK. In: Climate Policy, 22(8), pp. 1000–1015.

Best, H. (2011): Methodische Herausforderungen: Umweltbewusstsein, Feldexperimente und die Analyse umweltbezogener Entscheidungen. In: Groß, M. [Eds.] Handbuch Umweltsoziologie. VS Verlag für Sozialwissenschaften, Wiesbaden, pp. 240–258.

Best, H./Mayerl, J. (2013): Values, Beliefs, Attitudes: An Empirical Study on the Structure of Environmental Concern and Recycling Participation. In: Social Science Quarterly, 94(3), pp. 691–714.

BMU/BfN (2020): Naturbewusstsein 2019 – Bevölkerungsumfrage zu Natur und biologischer Vielfalt.

BMU/UBA (2019): Umweltbewusstsein in Deutschland 2018 – Ergebnisse einer repräsentativen Bevölkerungsumfrage.

BMUV/UBA (2023): Umweltbewusstsein in Deutschland 2022 – Ergebnisse einer repräsentativen Bevölkerungsumfrage.

Bohnenberger, K. (2023): Peaks and gaps in eco-social policy and sustainable welfare: A systematic literature map of the research landscape. In: European Journal of Social Security, 25(4), pp. 328–346.

Bollen, K. A./Curran, P. J. (2006): Latent curve models: A structural equation perspective. Hoboken, N.J: Wiley-Interscience.

Bosnjak, M./Dannwolf, T./Enderle, T. [Eds.] (2018): Establishing an Open Probability-Based Mixed-Mode Panel of the General Population in Germany. In: Social Science Computer Review, 36(1), pp. 103–115.

Boudet, H. S. (2019): Public perceptions of and responses to new energy technologies. In: Nature Energy, 4(6), pp. 446–455.

Brandmaier, A. M./Jacobucci, R. C. (2023): Machine learning approaches to structural equation modeling. In: Hoyle, R. H. [Eds.]: Handbook of structural equation modeling. Second edition, New York: The Guilford Press, pp. 722–739.

Brandmaier, A. M./Oertzen, T. von/McArdle, J. J./Lindenberger, U. (2013): Structural equation model trees. In: Psychological methods, 18(1), pp. 71–86.

Brandmaier, A. M./Prindle, J. J./Arnold, M./van Lissa, C. J. (2023): semtree: Recursive Partitioning for Structural Equation Models. Online: https://github.com/brandmaier/semtree. [Date of Access: 01.09.2024].

Breukers, S./Wolsink, M. (2007): Wind power implementation in changing institutional landscapes: An international comparison. In: Energy Policy, 35(5), pp. 2737–2750.

Carley, S./Konisky, D. M./Atiq, Z./Land, N. (2020): Energy infrastructure, NIMBYism, and public opinion: a systematic literature review of three decades of empirical survey literature. In: Environmental Research Letters, 15(9), 93007.

Cheung, G. W./Rensvold, R. B. (2002): Evaluating Goodness-of-Fit Indexes for Testing Measurement Invariance. In: Structural Equation Modeling: A Multidisciplinary Journal, 9(2), pp. 233–255.

Curran, P. J./Obeidat, K./Losardo, D. (2010): Twelve Frequently Asked Questions About Growth Curve Modeling. In: Journal of cognition and development, 11(2), pp. 121–136.

Dauvergne, P. (2018): Environmentalism of the rich. Cambridge: MIT Press

Dehler-Holland, J./Schumacher, K./Fichtner, W. (2021): Topic Modeling Uncovers Shifts in

Media Framing of the German Renewable Energy Act. In: Patterns, 2(1), 100169.

Devine-Wright, P. (2005): Beyond NIMBYism: Towards an integrated framework for understanding public perceptions of wind energy. In: Wind Energy, 8(2), pp. 125–139.

Devine-Wright, P. (2007): Reconsidering public attitudes and public acceptance of renewable energy technologies: a critical review.

Dunlap, R. E./van Liere, K. D. (1978): The New Environmental Paradigm: A Proposed Measuring Instrument and Preliminary Results. In: The New Environmental Paradigm, 9(4), pp. 10–19.

Dunlap, R. E./van Liere, K. D./Mertig, A. G./Jones, R. E. (2000): Measuring Endorsement of the New Ecological Paradigm: A Revised NEP Scale. In: Journal of Social Issues, 56(3), pp. 425–442.

Eichenauer, E./Gailing, L. (2022): What Triggers Protest?—Understanding Local Conflict Dynamics in Renewable Energy Development. In: Land, 11(10), 1700.

Ellis, G./Määttä, S./Batel, S. [Eds.] (2023): Social Acceptance Research Guide. Zenodo.

Engels, A./Hüther, O./Schäfer, M./Held, H. (2013): Public climate-change skepticism, energy preferences and political participation. In: Global Environmental Change, 23(5), pp. 1018–1027.

Fraune, C./Knodt, M. (2018): Sustainable energy transformations in an age of populism, post-truth politics, and local resistance. In: Energy Research & Social Science, 43, pp. 1–7.

Grimm, K. J./Ram, N. (2009): A Second-Order Growth Mixture Model for Developmental Research. In: Research in Human Development, 6(2-3), pp. 121–143.

Gürtler, K./Herberg, J. (2023): Moral rifts in the coal phase-out—how mayors shape distributive and recognition-based dimensions of a just transition in Lusatia. In: Journal of Environmental Policy & Planning, 25(2), pp. 194–209.

Gürtler, K./Löw Beer, D./Herberg, J. (2021): Scaling just transitions: Legitimation strategies in coal phase-out commissions in Canada and Germany. In: Political Geography, 88, 102406.

Haas, T./Herberg, J./Löw-Beer, D. (2022): From carbon democracy to post-fossil capitalism? The German coal phase-out as a crossroads of sustainability politics. In: Sustainability Science, Practice and Policy, 18(1), pp. 384–399.

Haggett, C. (2011): Understanding public responses to offshore wind power. In: Energy Policy, 39(2), pp. 503–510.

Hanke, F./Grossmann, K./Sandmann, L. (2023): Excluded despite their support - The perspectives of energy-poor households on their participation in the German energy transition narrative. In: Energy Research & Social Science 104, 103259.

Harper, M./Anderson, B./James, P. A./Bahaj, A. S. (2019): Onshore wind and the likelihood of planning acceptance: Learning from a Great Britain context. In: Energy Policy, 128, pp. 954–966.

Jacobucci, R./Grimm, K. J./McArdle, J. J. (2017:) A Comparison of Methods for Uncovering Sample Heterogeneity: Structural Equation Model Trees and Finite Mixture Models. In: Structural Equation Modeling: A Multidisciplinary Journal, 24(2), pp. 270–282.

Jagers, S. C./Harring, N./Matti, S. (2018): Environmental management from left to right – on ideology, policy-specific beliefs and pro-environmental policy support. In: Journal of Environmental Planning and Management, 61(1), pp. 86–104.

Janik, A./Ryszko, A./Szafraniec, M. (2021): Determinants of the EU Citizens' Attitudes towards the European Energy Union Priorities. In: Energies, 14(17), 5237.

Jenkins, K./McCauley, D./Heffron, R./Stephan, H./Rehner, R. (2016): Energy justice: A conceptual review. In: Energy Research & Social Science, 11, pp. 174–182.

Jones, C. R./Eiser, J. R. (2009): Identifying predictors of attitudes towards local onshore wind development with reference to an English case study. In: Energy Policy, 37(11), pp. 4604–4614.

Judge, M./Kashima, Y./Steg, L./Dietz, T. (2023): Environmental Decision-Making in Times of Polarization.

In: Annual Review of Environment and Resources, 48(1), pp. 477–503.

Krause, T. (2019): Multiple Indicator Growth Mixture Models: eine statistische Simulation zur Performanzevaluation für sozialwissenschaftliche Analysen. Stuttgart: Universität Stuttgart.

Krüger, T./Eichenauer, E./Gailing, L. (2022): Whose future is it anyway? Struggles for just energy futures. In: Futures, 142, 103018.

Levi, S./Wolf, I./Sommer, S./Howe, P. D. (2023): Local support of climate change policies in Germany over time. In: Environmental Research Letters, 18(6), 64046.

Liebe, U./Dobers, G. M. (2019): Decomposing public support for energy policy: What drives acceptance of and intentions to protest against renewable energy expansion in Germany? In: Energy Research & Social Science, 47, pp. 247–260.

Little, T. D. (2013): Longitudinal Structural Equation Modeling. Guilford Publications, New York.

Lux, T., Mau, S./Jacobi, A. (2022) Neue Ungleichheitsfragen, neue Cleavages? Ein internationaler Vergleich der Einstellungen in vier Ungleichheitsfeldern. In: Berliner Journal für Soziologie, 32(2), pp. 173–212.

McArdle, J. J./Epstein, D. (1987): Latent Growth Curves within Developmental Structural Equation Models. In: Child Development, 58(1), pp. 110–133.

Meredith, W./Horn, J. (2001): The role of factorial invariance in modeling growth and change. In: Collins, L. M./Sayer, A. G. [Eds.] New methods for the analysis of change. Washington: American Psychological Association, pp. 203–240.

Meredith, W./Tisak, J. (1990): Latent curve analysis. In: Psychometrika, 55(1), pp. 107–122.

Müller, M./Schulze, M./Schöneich, S. (2023): The energy transition and green mineral value chains: Challenges and opportunities for Africa and Latin America. In: South African Journal of International Affairs, 30(2), pp. 169–175.

Muthén, L. K./Muthén, B. O. (2002): How to Use a Monte Carlo Study to Decide on Sample Size and Determine Power. In: Structural Equation Modeling: A Multidisciplinary Journal, 9(4), pp. 599–620.

Osberghaus, D./Achtnicht, M./Bubeck, P. [Eds.] (2020): Klimawandel in Deutschland: Risikowahrnehmung und Anpassung in privaten Haushalten 2020.

Oswald, M. T./Fromm, M./Broda, E. (2021): Strategic clustering in right-wing-populism? ‘Green policies’ in Germany and France. In: Zeitschrift für Vergleichende Politikwissenschaft, 15(2), pp. 185–205.

Preacher, K./Wichman, A./MacCallum, R./Briggs, N. (2008): Latent Growth Curve Modeling. Thousand Oaks: Sage.

Radtke, J./Canzler, W./Schreurs, M. A./Wurster, S. [Eds.] (2019): Energiewende in Zeiten des Populismus. Wiesbaden: Springer VS.

Ramasar, V./Busch, H./Brandstedt, E./Rudus, K. (2022): When energy justice is contested: A systematic review of a decade of research on Sweden's conflicted energy landscape. In: Energy Research & Social Science, 94, 102862.

Rand, J./Hoen, B. (2017): Thirty years of North American wind energy acceptance research: What have we learned? In: Energy Research & Social Science, 29, pp. 135–148.

Ratter, B./Runge, A. (2022): Klimawandelwahrnehmung und Extremereignisse in Deutschland, 2022. Hamburg: University of Hamburg.

Reusswig, F./Braun, F./Heger, I./Ludewig, T./Eichenauer, E./Lass, W. (2016): Against the wind: Local opposition to the German Energiewende. In: Utilities Policy, 41, pp. 214–227.

Rogosa, D. R./Willett, J. B. (1985): Understanding correlates of change by modeling individual differences in growth. In: Psychometrika, 50(2), pp. 203–228.

Rosseel, Y. (2012): lavaan: An R Package for Structural Equation Modeling. In: Journal of Statistical Software, 48(2), pp. 1–36.

Ruddat, M. (2022): Public acceptance of wind energy – concepts, empirical drivers and some open questions. In: Wind Energy Science, 7(4), pp. 1679–1691.

Ruddat, M./Sonnberger, M. (2015): Wie die Bürgerinnen und Bürger ihre Rolle bei der Energiewende sehen. In: Energiewirtschaftliche Tagesfragen, 65(1/2), pp. 121–125.

Rutkowski, L./Svetina, D. (2014): Assessing the Hypothesis of Measurement Invariance in the Context of Large-Scale International Surveys. In: Educational and Psychological Measurement, 74(1), pp. 31–57.

Setton, D. (2019): Soziales Nachhaltigkeitsbarometer der Energiewende 2018. Kernaussagen und Zusammenfassung der wesentlichen Ergebnisse. Potsdam: Institut für transformative Nachhaltigkeitsforschung (IASS).

Sommer, B./Schad, M./Kadelke, P./Humpert, F./Möstl, C. (2022): Rechtspopulismus vs. Klimaschutz?: Positionen, Einstellungen, Erklärungsansätze. München: oekom Verlag.

Sonnberger, M./Ruddat, M. (2016): Die gesellschaftliche Wahrnehmung der Energiewende: Ergebnisse einer deutschlandweiten Repräsentativbefragung, Stuttgart.

Sonnberger, M./Ruddat, M. (2017): Local and socio-political acceptance of wind farms in Germany. In: Technology in Society, 51, pp. 56–65.

Sonnberger, M./Ruddat, M. (2018): Disclosing Citizens' Perceptual Patterns of the Transition to Renewable Energy in Germany. In: Nature and Culture, 13(2), pp. 253–280.

Sovacool, B. K. (2014): What are we doing here?: Analyzing fifteen years of energy scholarship and proposing a social science research agenda. In: Energy Research & Social Science, 1, pp. 1–29.

Steentjes, K./Pidgeon, N./Poortinga, W. [Eds.] (2017): European Perceptions of Climate Change: Topline findings of a survey conducted in four European countries in 2016, Cardiff.

Stekhoven, D. J./Bühlmann, P. (2012): MissForest--non-parametric missing value imputation for mixed-type data. In: Bioinformatics, 28(1), pp. 112–118.

Stern, P. C./Dietz, T. (1994): The Value Basis of Environmental Concern. In: Journal of Social Issues, 50(3), pp. 65–84.

Swofford, J./Slattery, M. (2010): Public attitudes of wind energy in Texas: Local communities in close proximity to wind farms and their effect on decision-making. In: Energy Policy, 38(5), pp. 2508–2519.

Thomas, M./DeCillia, B./Santos, J. B./Thorlakson, L. (2022): Great expectations: Public opinion about energy transition. In: Energy Policy, 162, 112777.

UBA (2021): 25 Jahre Umweltbewusstseinsforschung im Umweltressort: Langfristige Entwicklungen und aktuelle Ergebnisse.

Urban, D. (2004): Neue Methoden der Längsschnittanalyse: Zur Anwendung von latenten Wachstumskurvenmodellen in Einstellungs- und Sozialisationsforschung. Münster: LIT.

Usami, S./Jacobucci, R./Hayes, T. (2019): The performance of latent growth curve model-based structural equation model trees to uncover population heterogeneity in growth trajectories. In: Computational Statistics, 34(1), pp. 1–22.

Wahl, A. (2020): Multiple Imputation by Chained Equations - eine Leistungsevaluation bei Schätzung von Strukturgleichungsmodellen mittels Monte-Carlo-Simulationen. Stuttgart: Universität Stuttgart.

Walter, G./Gutscher, H. (2013): Generelle Befürwortung von Windkraftanlagen vor Ort vs. Befürwortung spezifischer Windkraftprojekte: Der Einfluss von Projekt- und Verfahrensparametern. In: Umweltpsychologie, 17(2), pp. 124–144.

Wickrama, K. A. S./Lee, T. K./O'Neal, C. W./Lorenz, F. O. (2016): Higher-order growth curves and mixture modeling with Mplus: A practical guide. Abingdon: Routledge.

Wolf, I./Ebersbach, B./Huttarsch, J.-H. (2023): Soziales Nachhaltigkeitsbarometer der Energie- und Verkehrswende 2023: Was die Menschen in Deutschland bewegt – Ergebnisse einer Panelstudie zu den Themen Energie und Verkehr.

Wolf, I./Huttarsch, J.-H./Fischer, A.-K./Ebersbach, B. (2022): Das Soziale Nachhaltigkeitsbarometer der Energie- und Verkehrswende 2022. Was die Menschen in Deutschland bewegt – Ergebnisse einer Panelstudie zu den Themen Energie und Verkehr.

Wolsink, M. (2000): Wind power and the NIMBY-myth: institutional capacity and the limited significance of public support. In: Renewable Energy, 21(1), pp. 49–64.

Wolsink, M. (2007): Wind power implementation: The nature of public attitudes: Equity and fairness instead of ‘backyard motives’. In: Renewable and Sustainable Energy Reviews, 11(6), pp. 1188–1207.

Appendix

MODEL	X^2	DF	AIC	BIC	CFI	CFI (SCA-LED)	RMSEA	RMSEA (SCALED)	SRMR
CONFIG INVARIANT	3666.061	1125	337539.2	340169.9	0.9725115	0.9738411	0.02305892	0.01964271	0.03613635
METRIC INVARIANT	3777.480	1165	337570.6	339947.1	0.9717389	0.9729811	0.02297583	0.01961726	0.03844000
SCALAR INVARIANT	4225.682	1205	337938.8	340061.1	0.9673231	0.9680905	0.02429219	0.02096207	0.03954542

Table 4: Comparison of model fit indices for longitudinal measurement invariance test

Note: The indices include chi-square (χ^2), degrees of freedom (df), Akaike information criterion (AIC), Bayesian information criterion (BIC), comparative fit index (CFI), root mean square error of approximation (RMSEA) and standardized root mean square residual (SRMR). Adjusted values for CFI and RMSEA are also provided.

lhs	rhs	Unstd. Est.	SE	Std. Est.
I	w_b	1.000	0.000	0.908
I	w_c	1.000	0.000	0.936
I	w_d	1.000	0.000	0.929
I	w_e	1.000	0.000	0.919
I	w_f	1.000	0.000	0.909
I	w_g	1.000	0.000	0.849
I	w_h	1.000	0.000	0.842
I	w_i	1.000	0.000	0.780
I	w_j	1.000	0.000	0.740
S	w_b	0.000	0.000	0.000
S	w_c	-0.569	0.256	-0.050
S	w_d	-0.034	0.290	-0.003
S	w_e	0.771	0.330	0.067
S	w_f	2.210	0.316	0.190
S	w_g	4.660	0.315	0.374
S	w_h	5.426	0.339	0.431
S	w_i	7.819	0.311	0.576
S	w_j	8.000	0.000	0.559
w_b	bczd023a	1.000	0.000	0.568
w_b	bczd024a	1.193	0.018	0.747
w_b	bczd028a	0.743	0.018	0.573
w_b	bczd029a	0.896	0.019	0.589
w_b	bczd031a	1.089	0.018	0.730
w_b	bczd032a	0.838	0.023	0.524
w_c	cczd020a	1.000	0.000	0.568
w_c	cczd021a	1.193	0.018	0.764
w_c	cczd025a	0.743	0.018	0.573
w_c	cczd026a	0.896	0.019	0.605
w_c	cczd028a	1.089	0.018	0.733
w_c	cczd029a	0.838	0.023	0.521
w_d	dczd020a	1.000	0.000	0.567
w_d	dczd021a	1.193	0.018	0.771
w_d	dczd025a	0.743	0.018	0.578

lhs	rhs	Unstd. Est.	SE	Std. Est.
w_d	dczd026a	0.896	0.019	0.593
w_d	dczd028a	1.089	0.018	0.749
w_d	dczd029a	0.838	0.023	0.527
w_e	eczd020a	1.000	0.000	0.585
w_e	eczd021a	1.193	0.018	0.779
w_e	eczd025a	0.743	0.018	0.589
w_e	eczd026a	0.896	0.019	0.617
w_e	eczd028a	1.089	0.018	0.752
w_e	eczd029a	0.838	0.023	0.535
w_f	fczd020a	1.000	0.000	0.575
w_f	fczd021a	1.193	0.018	0.768
w_f	fczd025a	0.743	0.018	0.593
w_f	fczd026a	0.896	0.019	0.624
w_f	fczd028a	1.089	0.018	0.758
w_f	fczd029a	0.838	0.023	0.535
w_g	gczd020a	1.000	0.000	0.611
w_g	gczd021a	1.193	0.018	0.802
w_g	gczd025a	0.743	0.018	0.638
w_g	gczd026a	0.896	0.019	0.653
w_g	gczd028a	1.089	0.018	0.770
w_g	gczd029a	0.838	0.023	0.567
w_h	hczd019a	1.000	0.000	0.631
w_h	hczd020a	1.193	0.018	0.816
w_h	hczd024a	0.743	0.018	0.631
w_h	hczd025a	0.896	0.019	0.670
w_h	hczd027a	1.089	0.018	0.766
w_h	hczd028a	0.838	0.023	0.584
w_i	ibzd019a	1.000	0.000	0.655
w_i	ibzd020a	1.193	0.018	0.841
w_i	ibzd024a	0.743	0.018	0.664
w_i	ibzd025a	0.896	0.019	0.695
w_i	ibzd027a	1.089	0.018	0.797
w_i	ibzd028a	0.838	0.023	0.626
w_j	jbzd019a	1.000	0.000	0.679
w_j	jbzd020a	1.193	0.018	0.858
w_j	jbzd024a	0.743	0.018	0.694
w_j	jbzd025a	0.896	0.019	0.722
w_j	jbzd027a	1.089	0.018	0.793
w_j	jbzd028a	0.838	0.023	0.649

Table 5: Factor loadings of the unconditional growth curve model
Note: n=4248 with FIML missings treatment.

Variable / variable categories	Mean/ percentage	SD	n
Gender			
Male	49.3%		3746
Female (reference)	50.7%		3853
Household net income			
700 € >=	1.7%		83
700 - 900 €	1.3%		67
900 - 1100 €	2.3%		117
1100 - 1300 €	3.8%		192
1300 - 1500 €	3.5%		175
1500 - 1700 €	5.2%		261
1700 - 2000 €	8.2%		408
2000 - 2300 €	9.9%		495
2300 - 2600 €	10.3%		516
2600 - 3200 €	15.3%		764
3200 - 4000 €	15.6%		781
4000 - 5000 €	11.2%		558
5000 - 6000 €	6.3%		317
6000 € =<	5.3%		267
Households with children under 16			
Yes	34.9%		2231
No	65.1%		4158
Household social class perception			
Lower class	6.8%		511
Working class	34.1%		2563
Middle class	46.7%		3508
Upper middle class	10.3%		771
Upper class	2.1%		157
Left-right scale a	4.6	2.0	4806
Political interest b	2.9	0.9	4901
Residence categorization			
Big city	13.0%		640
Outskirts or suburbs of a big city	15.0%		737
Medium-sized or small town	40.2%		1979
Rural village	30.4%		1496
Single farmstead or detached house in the countryside	1.4%		70
Year of birth	1968.5	14.7	7545
Nationality			
Germany	92.3%		7001
EU28	3.3%		252
Rest of Europe	2.7%		203
Other	1.7%		131
Highest educational degree			
Student	0.5%		35

Variable / variable categories	Mean/ percentage	SD	n
Left school without degree	2.2%		168
Lower secondary school	23.7%		1777
Secondary school	26.6%		1997
Polytechnic secondary school GDR, 8th or 9th grade	1.5%		109
Polytechnic secondary school GDR, 10th grade	7.6%		573
Advanced technical college certificate	8.9%		671
General qualification for university entrance	29.0%		2180
Household size			
1	15.7%		1193
2	35.8%		2709
3	21.6%		1634
4	18.4%		1391
5=<	8.6%		650
NEP scale c			
We are approaching the limit of the number of people the earth can support.	2.5	1.0	4049
Humans have the right to modify the natural environment to suit their needs.	3.4	1.0	4055
When humans interfere with nature it often produces disastrous consequences.	1.8	0.8	4062
Human ingenuity will ensure that we do not make the earth unlivable.	3.0	1.0	4037
Humans are severely abusing the environment.	1.9	0.8	4054
There are enough natural resources on the planet – we just have to learn how to use them.	2.5	1.1	4050
Plants and animals have as much right as humans to exist.	1.8	0.8	4061
The balance of nature is strong enough to cope with the impacts of modern industrial nations.	3.9	0.9	4055
Despite our special abilities, humans are still subject to the laws of nature.	1.7	0.6	4065
The so-called “ecological crisis” facing humankind has been greatly exaggerated.	3.6	1.0	4050
The earth is like a spaceship with very limited room and resources.	2.1	0.9	4048
Humans were meant to rule over the rest of nature.	3.9	1.0	4044
The balance of nature is very delicate and easily upset.	1.9	0.8	4057
Humans will eventually learn enough about how nature works to be able to control it.	3.5	0.9	4046
If things continue on their present course, we will soon experience a major ecological catastrophe.	2.1	0.9	4059

Table 6: Descriptive characteristics of independent variables

Note: All values are based on data from survey wave a (2013) except NEP items (wave b 2014); a answering scale: 0 = left, 10 = right; b answering scale: 1 = very strong, 5 = none at all; c answering scale: 1 = fully agree, 5 = fully disagree

Items	2014		2015		2016		2017		2018		2019		2020		2021		2022	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Renewable energies are simply not sufficient to supply an industrial country.	3.0	1.1	3.1	1.1	3.1	1.1	3.1	1.0	3.0	1.1	3.0	1.1	3.1	1.1	3.0	1.1	2.9	1.1
The so-called “energy transition” does more harm than good.	3.3	1.0	3.4	0.9	3.4	1.0	3.5	0.9	3.4	0.9	3.4	1.0	3.4	1.0	3.4	1.0	3.4	1.1
The future lies in renewable energies.	2.0	0.8	2.0	0.8	2.0	0.8	2.0	0.8	2.0	0.8	2.0	0.8	2.0	0.8	2.0	0.8	2.0	0.8
All energy-saving measures are ultimately exaggerated.	3.6	1.0	3.7	0.9	3.7	0.9	3.7	0.9	3.8	0.9	3.7	0.9	3.8	0.9	3.7	0.9	3.7	0.9
The energy transition is destroying Germany’s industrialbase.	3.5	0.9	3.6	0.9	3.6	0.9	3.6	0.9	3.6	0.9	3.4	1.0	3.5	1.0	3.4	1.0	3.3	1.0
There is noalternative to switching to renewableenergies.	2.5	1.0	2.5	1.0	2.4	1.0	2.4	1.0	2.4	1.0	2.5	1.0	2.4	1.0	2.5	1.0	2.5	1.0

Table 7: Descriptive characteristics of dependent variable items from wave b (2014) to wave j (2022)

Note: Answering scale: 1 = fully agree, 5 = fully disagree

NEP Score	-	0.06	-0.05	-0.00	-0.05	-0.01	0.00	-0.02	-0.11***	-0.04	0.07*	-0.03
Gender (Male)	0.06*	-	0.10***	-0.04	-0.03	0.23***	-0.01	-0.02	0.02	-0.02	0.06**	-0.02
Household Income	-0.05*	0.10***	-	0.03	0.32***	0.20***	0.01	0.03	0.13***	0.36***	0.03	0.18***
Children Under 16	-0.00	-0.04**	0.03*	-	-0.02	-0.08***	0.01	-0.29***	-0.11***	0.05***	-0.02	0.58***
Household Class Perception	-0.05*	-0.03*	0.32***	-0.02	-	0.14***	0.04	0.05**	0.11***	0.26***	0.04	0.04
Political Interest	-0.01	0.23***	0.20***	-0.08***	0.14***	-	0.08***	0.24***	0.10***	0.20***	-0.01	-0.08***
Residence Categorization	0.00	-0.01	0.01	0.01	0.04**	0.08***	-	-0.03	-0.06***	0.16***	-0.06***	-0.14***
Age	-0.02	-0.02	0.03*	-0.29***	0.05***	0.24***	-0.03*	-	0.09***	-0.17***	0.03	-0.28***
German Citizenship	-0.11***	0.02	0.13***	-0.11***	0.11***	0.10***	-0.06***	0.09***	-	0.10***	-0.02	-0.08***
Highest Education	-0.04	-0.02	0.36***	0.05***	0.26***	0.20***	0.16***	-0.17***	0.10***	-	-0.06***	0.01
Left-Right Scale	0.07**	0.06***	0.03	-0.02	0.04*	-0.01	-0.06***	0.03*	-0.02	-0.06***	-	0.02
Household Size	-0.03	-0.02	0.18***	0.58***	0.04**	-0.08***	-0.14***	-0.28***	-0.08***	0.01	0.02	-
Variable	NEP Score	Gender (Male)	House-hold Income	Children Under 16	House-hold Class Percep-tion	Political Interest	Resi-dence Catego-rization	Age	German Citizens-hip	Highest Educa-tion	Left-Right Scale	House-hold Size

Table 8: Pairwise Correlation Matrix (Pearson, Phi, and Point-Biserial Correlations Based on Measurement Scales) of Independent Predictors

*Note: Pairwise sample sizes range from 1373 to 7599 across the variables. *p < .05, **p < .01, ***p < .001. (Two-tailed tests)*

Autoren:

Marco Sonnberger *is a lecturer at the Department of Sociology of Technology, Risk and Environment at the University of Stuttgart.*
marco.sonnberger@sowi.uni-stuttgart.de

Thomas Krause *is a postdoctoral researcher at the Institute of Social Sciences at the University of Stuttgart, specializing in social science research methods.*
thomas.krause@sowi.uni-stuttgart.de

Michael Ruddat *is a research associate at the Research Center for Interdisciplinary Risk and Innovations Studies (ZIRI-US) at the University of Stuttgart.*
michael.ruddat@zirius.uni-stuttgart.de

Impressum

Soziologie und Nachhaltigkeit
Beiträge zur sozial-ökologischen Transformationsforschung

ISSN 2364-1282
Heft 1/2025, 11.Jahrgang, DOI: 10.17879/sun-2025-6375
Eingereicht 10.01.2024 – Peer-Review 30.07.2024 – Überarbeitet 29.10.2024 – Akzeptiert 11.12.2024

Herausgeber*innen: Benjamin Görgen, Matthias Grundmann, Anna Henkel, Melanie Jaeger-Erben, Bernd Sommer, Björn Wendt

Redaktion: Raphaela Casata, Niklas Haarbusch, Andreas Huber, Jakob Kreß, Carsten Ohlrogge, Marcel Sebastian

Layout/Satz: Nele Burghardt, Niklas Haarbusch

Anschrift: Universität Münster, Institut für Soziologie
Scharnhorststraße 121, 48151 Münster
Telefon: (0251) 83-25440
E-Mail: sun.redaktion@uni-muenster.de
Website: www.sun-journal.org

Gefördert durch die Deutsche Forschungsgemeinschaft (DFG) - Projektnummer 490954504