Energy 239 (2022) 122150

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

The social acceptance of shale gas development: Evidence from Turkey

Dilge Güldehen Kânoğlu-Özkan [a, b], Uğur Soytaş [b, c, d, *]

[a] The University of Texas at Austin, Energy and Earth Resources, Austin, TX, USA
[b] Middle East Technical University, Earth System Science Program, Ankara, Turkey
[c] Middle East Technical University, Department of Business Administration, Ankara, Turkey
[d] Technical University of Denmark, Department of Technology, Management, and Economics, Copenhagen, Denmark

A R T I C L E I N F O

Article history:
Received 5 March 2021
Received in revised form
20 September 2021
Accepted 21 September 2021
Available online 27 September 2021

Keywords:
Social acceptance
Shale gas
Hydraulic fracturing
Information
Partial least squares

A B S T R A C T

Social acceptance can have an important impact on the market penetration of energy technologies and the successful implementation of energy policies. Hence, it is essential to develop quantitative measures of acceptance to be able to manage it. This study adopts a behavioral model to examine the antecedent factors of the social acceptance of shale gas development in Turkey. It utilizes data from a structured questionnaire to estimate a partial least squares model that is based on psychological factors that impact acceptance. This study then explores the influence of the source and content of information on shale gas acceptance. The model results indicate that environmental problem perception and perceived costs do not have a significant effect on the social acceptance of shale gas development. The results have important implications for policymakers as well. The analysis demonstrates that attitudes may be changed through selecting an adequate means of communication between professional actors and society. Effective communication may reduce anxiety about risks associated with shale gas development by allowing individuals to develop a better understanding of the technology. The analysis also suggests that information provision by scientists may prevent the utilization of previous experiences in constructing a knowledge base.

1. Introduction

Recent developments, particularly conflicts associated with energy technologies, have delineated that decision-makers should be considerate of important realities about human interactions with environmental, economic, and energy systems. While technological, economic, and environmental constraints to implementing low-carbon infrastructure projects will be important in the near term, the social acceptance of alternative solutions and the behavioral aspects of energy system transformations are most likely to be equally challenging. Individuals will need to alter their behavior, both at their residences and workplaces. Attitudes may dictate the ease of implementing policy interventions related to energy technologies [1]. Papadis and Tsatsaronis [2] emphasize that increased public acceptance of alternative solutions must accompany economic and environmental constraints to reach targets because the lack of acceptance may impose very high costs or eliminate very large gains.

Although the general opinion may be positive towards new energy projects, local acceptance may be lacking. Raven et al. [3] refer to this as a ‘social gap’. Despite its importance, quantifying social acceptance is a challenge due to difficulties in collecting data on indicators and quantifying factors that can be directly employed in technical analyses of the energy-economy-environment-society (3 ES) nexus. It is relatively easier to measure and monitor the 3 Es, but difficult to do so for the S dimension. Recent studies took on the challenge and used quantitative methods to study the social acceptance of different energy projects. Nevertheless, no single approach or group of metrics has emerged as best practice. For instance, Savvanidou et al. [4] studied perceptions of biofuels in Greece using data gathered from face-to-face interviews. On the other hand, Musall and Kuik [5] analyzed the influence of a community co-ownership model on the local acceptance of renewable energy in Germany. Another study by Bhowmik et al. [6] explored the determinants of “green energy” acceptance in the Tripura

* Corresponding author. Middle East Technical University, Earth System Science Program, Ankara, Turkey.
E-mail address: uguso@dtu.dk (U. Soytaş).

https://doi.org/10.1016/j.energy.2021.122150
0360-5442/

region of India. Whereas Bertsch et al. [7] considered renewable energy acceptance in Germany. These studies used different quantitative methods.

Several acceptance studies focused on behavioral factors in explaining attitudes. Montijn-Dorgelo and Midden [8], studied the mediating role of negative affective associations and trust in the risk perception of hydrogen as an energy carrier in transportation. Midden and Huijts [9] included factors such as trust, positive and negative effects, perceived risks, and perceived benefits to explain attitudes towards CO2 storage. Similarly, Bronfman et al. [10] used behavioral factors such as trust, and risk and benefit perception and assessed the acceptance of electricity generation sources, though they did not differentiate between the methods of generation.

Some scholars examined attitudes via a combination of socio-demographic and behavioral factors. In investigating the influence of procedural and outcome fairness on the acceptance of nuclear power plants in Switzerland, Visschers and Siegrist [11] included socioeconomic variables such as age, gender, and education level alongside behavioral measures of risk perception, and benefit perception for the climate and the economy. Similarly, Ladenburg [12] included socioeconomic variables as well as geographical variables (i.e., zip code, region, city size, proximity to a wind turbine) in addition to belief-orientated variables in a probit model that explained attitudes towards on-land and offshore wind power development in Denmark.

This research aims to show how analytical approaches may be used to understand attitudes towards shale gas development and to identify factors that could guide public information. It follows the behavioral model framework proposed in Kânoğlu and Soytaş [13] and seeks to understand perceptions that underpin acceptability to provide a more generalizable, effective, and strategic approach to advocacy.

Opinion polls have offered valuable insight into the way people perceive shale gas development, though they have mainly studied attitudes in relation to sociodemographic variables [14,15] or spatial variables and how they interact with factors like economic, social, or environmental risks and benefits [16–18]. The relationship between geographic proximity and the acceptance of energy technologies has received a lot of attention from scholars. Yet, the literature presents mixed results for this relationship. Some studies have referred to the Not in My Backyard (NIMBY) phenomenon [19,20]. Others have argued that the NIMBY concept has become an "insufficient and overly simplistic explanation" for all types of opposition [21] and have provided examples for the "inverse NIMBY" [22] or "Yes in My Backyard" [23] response. Researchers also noted that social acceptance is a process of aligning a broad spectrum of personal, ideological, social, cultural, physical, contextual, political, and ideological factors, and coordinating solutions [24,25]. In the context of shale gas development, some studies found no relationship between geographic proximity and acceptance [26], while others found evidence supporting the inverse of NIMBY [27]. In fact, individuals who live in close proximity to development are more likely to exhibit more negative attitudes towards the industry when compared to individuals who reside in areas where the industry is less mature [28,29]. They are also more likely to perceive energy resource development as a necessity, and less likely to perceive development as an environmental threat [28]. The literature suggests that attitudes toward natural gas development are highly dependent on environmental attitudes, experience with industry, development, or employment [26,27], and economic opportunities [28,30].

Attitudes have high spatial variance at an individual level; hence researchers have also explored state-level differences [31]. The results of a study on two spatially adjacent states, New York, and Pennsylvania, pointed to the influence of location of the primary residence on the way they weigh the risks and benefits [31]. Research around how different communities view shale gas development is limited, most of which are conducted in the U.K. such as [15,32] and a series of follow up studies in 2013, 2015, and 2017 [33–35] and very recently in China [36]. These studies have, in addition to highlighting spatial differences in attitudes, underscored the dynamic nature of social acceptance by demonstrating that attitudes may vary at different stages of the project implementation [33–35]. They also claimed that the underlying reason for these variations may be knowledge, as sufficient knowledge is necessary for individuals to reach a reasoned judgment [32,33,35].

Several opinion polls tried to understand the relationship between knowledge and perceptions of hydraulic fracturing and most of these surveys have pointed out the lack of familiarity with shale gas development. For instance, Boudet et al. [14] noted that even though a large share of respondents indicated they had some amount of knowledge about the technology, only less than 10% could specify its environmental impacts such as water quality (7%); economic impacts such as employment opportunities and affordable energy (3%); and social impacts such as effects on property and individuals (1%). Studies in the UK [32,33] pointed to a probable relationship between information provision and attitude formation [32]. The University of Nottingham survey noted that the increase in peoples' familiarity with shale gas development, was associated with a change in the attitude towards the technology [33]. One weakness of the surveys intended at capturing this relationship is that they either noted changes in average responses of favorability metrics over time [33–35] and as exposure to information increases [32] or they reported results, which are based on socio-demographic, geographic [15,32] and familiarity measures [14], rather than establish the causal pathways that lead to changes in the attitude. Therefore, to provide guidance for policymakers to improve social acceptance, this study considers the impact of alternative forms and sources of information. The structured questionnaire is administered in Turkey, where shale gas development has not taken place and has not received a lot of attention from the media, and the results are then analyzed by the partial least squares (PLS) method. The results of the measurement and structural models are then compared and the policy implications of the findings are discussed.

Turkish energy demand relies heavily on fossil fuels (80%). Oil and coal account for 30% each, whereas natural gas meets 20% of energy demand. The IEA 2021 Turkey, Energy Policy Review points out that despite the recently discovered Sakarya reserve in the Black Sea region, and the bilateral agreements on gas pipelines from Russia, and Azerbaijan, Turkey will remain dependent on oil and gas imports. Hence, the country must utilize domestic resources fully to improve its energy security. In that respect, the country is assessing the potential of shale gas, gas hydrates, and coal bed methane in its overall energy mix. Currently, fracking is not restricted in Turkey. However, Energy Market Regulatory Authority may choose not to grant the license or may ask for additional guarantees. This paper contributes to the assessment of this largely unexplored potential by evaluating whether public acceptance can be a hindrance.

While there is no "one size fits all" solution [2,3], by providing an example of how behavioral and social criteria may be quantified such that they can be incorporated in multi-criteria assessments, this paper presents an approach that can be adapted to different types of energy technologies or different spatial settings.

2. Theoretical framework

Ajzen's theory of planned behavior [37] suggests that attitudes, subjective norms, and perceived behavioral control are critical dimensions in understanding the intention to exert a particular behavior. Attitudes refer to the extent to which a behavior is favorable, given that the behavior has positive or negative outcomes, while subjective norms refer to the influence of social pressures that urge the individual to perform or refrain from a behavior, and behavioral control refers to the ease of performing the behavior [37]. For this research, the behavior in question is narrowed down to expressing an opinion through responding to a questionnaire anonymously as there are no shale gas developments in Turkey yet. This eliminates any difficulty in performing the behavior and any social pressure that could urge individuals not to perform the behavior. Therefore, social norms and perceived behavioral control are excluded from the model. However, through the inclusion of an indicator for the degree of active promotion desired, attitudes are accounted for in the conceptual model.

Following Tokushige and Tomoda [38], who suggested that independent of the energy technology, the variance in levels of opposition and support could be attributed mainly to perceived risks, benefits and costs, these factors were included in the model. In this respect, development costs, risks such as surface and groundwater contamination and induced seismicity events [39], and benefits such as economic growth and increase in employment opportunities [40] are selected as relevant indicators. The perceived values of these factors influence attitudes towards shale gas development [37,41].

The norm activation model [42] is another theoretical framework that applies to the energy technology acceptance. Personal norms are activated when individuals recognize the negative consequences of not behaving in a socially desired way, and when they feel they may contribute to solving problems (i.e., outcome efficacy) [42]. As shale gas development has not been part of policy discussions in Turkey, and the behavior of interest is the expression of attitudes through responding to a questionnaire, there would be no feeling of moral obligation associated with the action. Hence, personal norms are not included in the model. Nonetheless, its antecedents, perceived benefits, risks and costs, outcome efficacy, and problem perception are considered [42,43]. Problem perception is another factor that could impact the social acceptance of shale gas development significantly [44,45]. The reasoning is that individuals who are more concerned about the prevention of global warming would favor a technology that reduces CO_2 emissions [45]. Outcome efficacy is also considered an important factor in explaining the acceptance of shale gas development [46].

Theories on affect constitute another important dimension of the conceptual model [47]. Peters and Slovic [48], and Montijn-Dorgelo and Midden [8] show that positive affect encompasses feelings like pride, happiness, satisfaction, and negative affect that blankets fear, worries, anger were independent and significant factors in predicting the acceptance of energy technologies. Contrarily, this study proposes evaluating affect through other factors in the model because these feelings are intertwined with environment or health concerns and perceived economic and social benefits associated with the energy technology in question. This is deemed appropriate because the negative affect “worry” resulting from natural gas' presence in taps [49] could be linked to safety concerns, lack of knowledge about shale gas, a lack of trust in the developers and regulators, or unfortunate experiences. Thus, integrating affective imagery into risk and benefit perception measures would serve to capture the relevance of affect as well.

Trust has a critical role in the conceptual model [50]. Prior research by Huijts et al. [44], concluded that when the public has little knowledge about the technology, and little desire to obtain more information, trust in professional actors becomes more important in explaining attitudes. They state that excessive trust could create more tolerance for uncertainties and a lack of it could diminish cooperation [44]. Following the literature [10,45,51], trust is linked to acceptance through perceived benefits, risks, and costs. In measuring trust, the factors that are commonly suggested by literature: the perceived intentions [10,44,52,53] and competence of professional actors [45,52–54], reliability [45], transparency in planning [5,53], ability to act without private or political pressures and obligations [10], the tendency to disclose information [45] and the degree to which the communicator will be truthful in the information communicated [54] are considered. This research follows the approach of Huijts et al. [44] and Montijn-Dorgelo and Midden [8] and treats trust in the industry and its regulators independently since the roles of these actors in the process of shale gas development are distinct.

The perceived distributive fairness [55,56], and procedural fairness are other crucial determinants [56,57]. In relation to distributive fairness, Schuitema et al. [55] suggest that fairness that is based on collective outcomes more strongly influences acceptance than fairness related to personal outcomes. Accordingly, this study focuses on the between-group distributions of benefits, risks, and costs. Procedural fairness is also relevant because it could potentially influence the perceived transparency and thus the trust dynamics of the decision process [58].

The experience factor has two pillars: one that encompasses the impacts associated with the technology directly [59], the other that encompasses the impacts perceived to generate concerns similar to those associated with shale gas development. For the first pillar, experience could serve as a means of accumulating knowledge. For instance, individuals residing in a region where shale gas development activity takes place may weigh the technology's risks and benefits more accurately [59]. For the latter, it could result in an erroneous evaluation of the risks and could influence acceptance significantly. An example of this could be the experience of an earthquake. Individuals who have previously experienced an earthquake could be more susceptible to oppose the technology if they are informed that the technology bears a seismic risk. The former pillar is not applicable to the case of Turkey because there are no shale projects in the region. Including this dimension where shale gas development has already taken place may be crucial.

Knowledge is also important because it is considered as a means of arriving at a sound judgment [60]. Survey data [14,32,33] underlines the deficiency of knowledge and the lack of a clear understanding of the risks associated with and benefits to be derived from shale gas development. Thus, this research explores the impact of information provision on acceptance. The study concentrates on two channels through which information provision could be influential, the source and content of information. Key actors involved in decision-making processes such as the government, industry, environmental NGOs, and scientists could instill a sense of security in local communities and reduce uncertainties [61]. A recent study by Wang et al. [62] confirmed this hypothesis for nuclear energy in China. Information publicity positively and directly impacts public acceptance and the relationship between them is dependent on the credibility of the information [62]. In terms of the content, certain details of an information package may not appeal to the audience. Based on a survey of Japanese university students, Tokushige et al. [45] discerned that information on natural analogues, and on-field demonstrations incremented the public acceptance of the geological storage of carbon. On the other hand, information concerning the scientific process of carbon storage did not influence attitudes [45]. To explore the validity of this argument, a graphical representation of the scientific process of shale gas development is included in one of the information packages in this study.

A conceptual model is constructed with perceived benefits, risks and costs, procedural and distributive fairness, trust, outcome efficacy, problem perception, knowledge, and experience constructs (see Fig. 1). For a more detailed discussion, the readers may refer to Kânoğlu and Soytaş [13].

3. Research method

3.1. Country

Turkey is a country where shale gas development has not started and hence the technology has received little to no attention from the media. The country's natural gas production in 2013 was equivalent to only 1.5% of its consumption [63]. Considering that Turkey has 24 trillion cubic feet of technically recoverable shale gas in the Southeastern and Thrace regions [64], it is possible to assert that the development of shale gas in the country could potentially reduce its foreign natural gas dependency.

3.2. Participant selection

The questionnaire was administered to the students, parents, alumni, faculty, and staff of Middle East Technical University (METU) of Ankara, Turkey. A convenience sampling approach was used. The survey respondents were reached at crowded locations on campus, which included classrooms, study halls, restaurants, libraries, and cafeterias. Their participation in the survey was entirely voluntary.

Whether undergraduate students are appropriate surrogates for non-student populations in consumer and behavioral research in general, is controversial. One argument is that college students systematically differ from nonstudents in that they are more homogeneous [65,66]. This homogeneity translates into stronger hypothesis tests than if non-student subjects are used, as there is less noise or variation associated with their responses [67]. Peterson [68] explored the validity of this argument and concluded that “the responses of college student subjects were slightly but consistently more homogeneous than those of nonstudent subjects, both within and across scales.” Furthermore, he found nearly half (48%) of the effect sizes obtained from college student respondents were significantly different from those derived from non-student respondents [68]. Mullinix et al. [69] explored how the magnitude of treatment effects produced by convenience samples compared to the effects derived from population samples and suggested that the causal effects are comparable. Hence, one should be cautious when using student samples and recognize the implications of the results, particularly if the research is intended at producing universal principles. Indeed, producing universal principles is not the aim of this research. This study starts with the conception that social acceptance shows spatial and temporal variance and intends to propose a method that is widely applicable. Then, by presenting a case study in Turkey, this study demonstrates the kind of results that may be derived from this generalizable approach.

Another important note is that the focus of this research is attitudes, not behavior. Beltramini [70] claimed that students are representative of adults or non-student samples in consumer research at the attitudinal level but are less appropriate as surrogates in research at the behavioral level. Hence, using a student sample is not expected to be inappropriate for this study. Though the results presented here are not universal, this study provides an approach for future research utilizing more generalizable samples.

3.3. Research approach

This study approached the social acceptance of shale gas development through testing deterministic propositions. In testing such relationships, surveys and case studies emerge as common approaches [71]. As this research intended to trace changes in acceptance and its antecedents as individuals were provided with information of different content from different sources, identifying relevant case studies would have been challenging. The main reason for this is that it would have required testing twelve different hypotheses, which would complicate the formulation of different settings that would allow the scrutiny of changes in all constructs. Consequently, conducting a survey was selected as the appropriate methodology. Responses were collected through paper surveys.

3.4. Survey questions

The questionnaire was designed to trace changes in the social acceptance of shale gas development and its antecedents. The

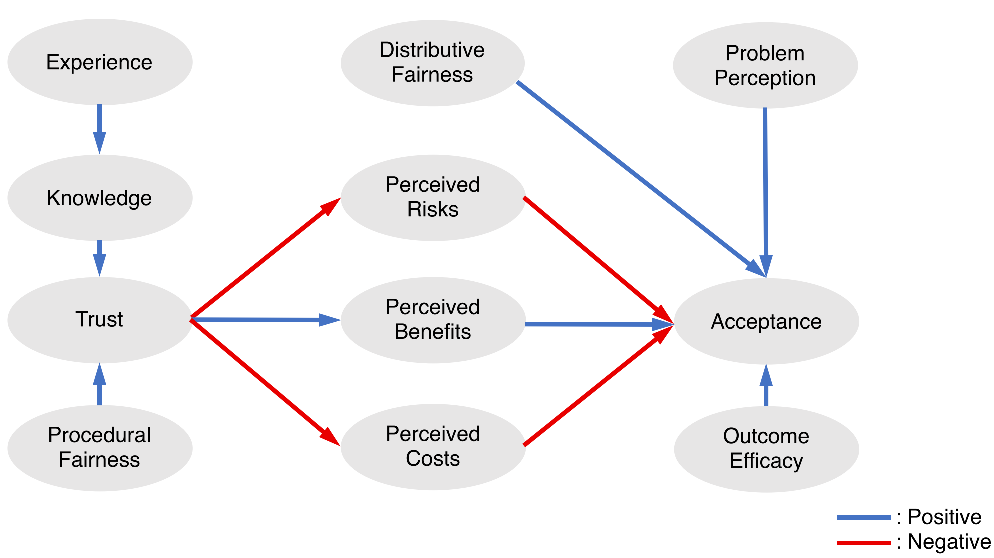

Fig. 1. An illustrative representation of the hypothesized relationships for the model of the social acceptance of shale gas development. The ellipses designate latent variables (i.e., perceived benefits, risks and costs, procedural and distributive fairness, trust, outcome efficacy, problem perception, knowledge, experience, and acceptance), and a single-headed arrow represents the direction of causality.

questions included represent latent factors in the conceptual model. While most were adapted from previous research, some were peculiar to this research (see Table 1). The item related to seismic risks, for instance, was self-constructed to capture perceptions of the risks that are frequently associated with shale gas development. Apart from the yes/no question for the experience indicator, the items in the questionnaire were measured on a five-point Likert-type scale with values ranging from "1: strongly disagree" to "5: strongly agree." In addition, a "0: don't know" option, which was treated as a missing response, was included in the survey so that individuals uninformed about the technology could be identified. All indicators were evaluated as reflective items, meaning that they changed in the same direction as the latent variable they were associated with. The adequacy of the measurement model was assessed initially with respect to the item and construct reliability values and then with respect to convergent and discriminant validities [72].

Table 1
Survey items and their foundations.

Survey Items	Papers Used
Experience E	
Disaster experience (E1)	Self-constructed
Knowledge (K)	
Sufficiency of climate change knowledge (K1)	Self-constructed
Sufficiency of shale gas knowledge (K2)	Self-constructed
Trust (T)	
Reliability (regulators) (T1)	Tokushige et al. (2007)
Reliability (operators) (T2)	Tokushige et al. (2007)
Disclosure of information about shale gas (regulators) (T3)	Frewer et al. (1996), Tokushige et al. (2007)
Disclosure of information about shale gas (operators) (T4)	Frewer et al. (1996), Tokushige et al. (2007)
Disclosure of information about alternatives to shale gas (regulators) (T5)	Self-constructed
Disclosure of information about alternatives to shale gas (operators) (T6)	Self-constructed
Intentions (regulators) (T7)	Bronfman et al. (2012), Huijts et al. (2007), Johnson (1999), Peters et al. (1997)
Intentions (operators) (T8)	Bronfman et al. (2012), Huijts et al. (2007), Johnson (1999), Peters et al. (1997)
Competence in assessment (regulators) (T9)	Bronfman et al. (2012), Frewer et al. (1996), Huijts et al. (2007), Johnson (1999), Peters et al. (1997), Tokushige et al. (2007)
Competence in assessment (operators) (T10)	Bronfman et al. (2012), Frewer et al. (1996), Huijts et al. (2007), Johnson (1999), Peters et al. (1997), Tokushige et al. (2007)
Ability to interfere when a problem arises (regulators) (T11)	Huijts et al. (2007), Tokushige et al. (2007)
Ability to solve problems (operators) (T12)	Bronfman et al. (2012), Huijts et al. (2007), Tokushige et al. (2007)
Safety concern (regulators) (T13)	Tokushige et al. (2007)
Safety concerns (operators) (T14)	Tokushige et al. (2007)
Transparency in planning (T15)	Musall and Kuik (2011), Peters et al. (1997)
Political independence (operators) (T16)	Bronfman et al. (2012)
Perceived Risks (R)	
Personal risk (R1)	Self-constructed following the approach of Tokushige et al. (2007)
Social risk (R2)	Self-constructed following the approach of Tokushige et al. (2007)
Environmental risk (R3)	Self-constructed following the approach of Huijts et al. (2007) and Tokushige et al. (2007)
Risk to future generations (R4)	Self-constructed following the approach of Tokushige et al. (2007)
Seismic risk (R5)	Self-constructed
Severity of consequences when a problem occurs (R6)	Tokushige et al. (2007)
Scientific knowledge about risks (R7)	Tokushige et al. (2007)
Perceived Benefits (B)	
Personal benefit (B1)	Tokushige et al. (2007)
Social benefit (B2)	Tokushige et al. (2007)
Environmental benefit (B3)	Bronfman et al. (2012), Huijts et al. (2007)
Benefit to future generations (B4)	Tokushige et al. (2007)
Economic benefit (B5)	Huijts (2012)
Development necessity (B6)	Tokushige et al. (2007)
Perceived Costs (C)	
Development costs (C1)	Huijts (2012)
Procedural Fairness (PF)	
Inclusion in decision making (PF1)	Huijts (2012)
Distributive Fairness (DF)	
Fair distribution of risks and benefits (DF1)	Huijts (2012)
Problem Perception (PP)	
Need for preventing global warming (PP1)	Tokushige et al. (2007)
Global warming as a concept against nature's laws (PP2)	Tokushige et al. (2007)
Global warming as a negative legacy from the development of civilization (PP3)	Tokushige et al. (2007)
Outcome Efficacy (OE)	
Consideration of opinions (OE1)	Huijts (2012)
Acceptance (A)	
Personal acceptance (A1)	Tokushige et al. (2007)
Social acceptance (A2)	Tokushige et al. (2007)
Acceptance of future generations (A3)	Tokushige et al. (2007)
Environmental acceptance (A4)	Bronfman et al. (2012)
Not in my back yard (NIMBY) (A5)	Tokushige et al. (2007)

3.5. Information provision

Data is collected from a control group that responded to the questionnaires without any information and a treatment group where participants were randomly provided with an information package that included either a summary of current discourses of key actors involved in the process of shale gas development, as in Huijts et al. [44] or a visual representation of the scientific process of shale gas development through hydraulic fracturing. The government, the industry, environmental NGOs, and scientists were identified as actors that could influence acceptance because they are involved in policymaking, the implementation of projects, the provision of information on environmental issues, and in the formulation of a shared fact base for the technology.

4. Data analysis

4.1. General information

Overall, 302 respondents completed the questionnaire for the control group, and 315 completed the survey for the information group. The gender distribution was balanced for both groups (145 females and 139 males for the control group; 144 females and 154 males for the information group). The respondents were relatively young with approximately 66 and 82% of respondents within the age range of 18–24 for the information and control groups, respectively. The participants were from engineering, economic, and administrative sciences disciplines.

4.2. Data screening: normality and outliers analysis

Responses for which more than 75% of the indicator values were missing, were removed from the data set. As the trust factor had many indicators, it was treated separately for the data screening process. Responses having more than 25% missing values were removed. The examination of histograms revealed no outliers. The normality of the distributions was analyzed to determine whether parametric or non-parametric tests should be used. Both Kolmogorov-Smirnov and Shapiro-Wilk tests indicated that all variables showed significant non-normality. Therefore, the data were analyzed using a non-parametric method called the partial least squares (PLS) technique [73].

4.3. Group-wise comparison

A comparison of the acceptance indicators of the information and the control groups was made to see whether there were significant differences in attitudes towards shale gas development. The mean acceptance values represented in Table 2 for the control ($\mu_{control} = 3.2$) and information ($\mu_{information} = 2.9$) group were on different ends of the acceptance spectrum. While on average, the control group displayed a favorable attitude towards shale gas development, the information group had a slightly negative attitude towards the technology.

A one-way ANOVA test identified differences between the means of the acceptance levels of different information groups. The post hoc Tukey and Bonferroni test results presented in Table 3 suggested that the means of acceptance of shale gas development close to one's house was significantly different for the control group and the group that received information from scientists. Additionally, the validity of the homogeneity of variances assumption was explored using the Levene statistic. The significance values suggested that the homogeneity of variance did not hold for the "development close to one's house" indicator. Yet, further analysis of the Kruskal Wallis test results suggested

Table 2
Basic descriptive statistics for the constructs. Abbreviations are listed as follows: E: Experience, K: Knowledge, T: Trust, PF: Procedural Fairness, DF: Distributive Fairness, R: Perceived Risks, B: Perceived Benefits, C: Perceived Costs, PP: Problem Perception, A: Acceptance, OE: Outcome Efficacy.

Type	E		PP		K		PF		OE		T		DF		C		R		B		A	
	Control	Info	Control	Info	Control	Info	Control	Info	Control	Info	Control	Info	Control	Info	Control	Info	Control	Info	Control	Info	Control	Info
Mean	0.360	0.440	4.320	4.390	3.460	3.520	2.520	2.360	2.590	2.440	2.570	2.580	2.780	2.610	3.300	3.360	3.300	3.160	3.030	2.860	3.200	2.900
Std. Error of Mean	0.050	0.057	0.086	0.100	0.097	0.109	0.089	0.121	0.106	0.122	0.106	0.105	0.109	0.108	0.087	0.099	0.095	0.118	0.114	0.114	0.092	0.115
Median	0.000	0.000	4.500	5.000	3.500	4.000	3.000	2.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000	3.000
Variance	0.233	0.250	0.680	0.767	0.866	0.911	0.736	1.129	1.036	1.145	1.040	0.851	1.095	0.899	0.698	0.761	0.829	1.081	1.197	0.992	0.774	1.015
Std. Deviation	0.482	0.500	0.824	0.876	0.931	0.954	0.858	1.063	1.018	1.070	1.020	0.923	1.046	0.948	0.835	0.872	0.911	1.040	1.094	0.996	0.880	1.008
Range	1.000	1.000	4.000	4.000	4.000	4.000	3.000	3.000	4.000	4.000	4.000	4.000	4.000	4.000	4.000	3.000	4.000	4.000	4.000	4.000	4.000	4.000
Skewness	0.599	0.240	−1.250	−1.823	−0.289	−0.477	−0.282	0.165	0.078	0.090	−0.053	−0.100	−0.020	0.197	−0.165	−0.057	−0.469	−0.321	−0.169	−0.279	0.098	−0.500
Std. Error of Skewness	0.251	0.274	0.251	0.274	0.251	0.274	0.251	0.274	0.251	0.274	0.251	0.274	0.251	0.274	0.251	0.274	0.251	0.274	0.251	0.274	0.251	0.274
Kurtosis	−1.678	−1.995	1.874	3.565	−0.141	−0.032	−0.566	−1.188	−0.621	−0.960	−0.836	−0.313	−0.500	−0.173	−0.247	−0.740	−0.105	−0.578	−0.422	−0.404	−0.420	−0.508
Std. Error of Kurtosis	0.498	0.541	0.498	0.541	0.498	0.541	0.498	0.541	0.498	0.541	0.498	0.541	0.498	0.541	0.498	0.541	0.498	0.541	0.498	0.541	0.498	0.541

Table 3
Intergroup comparison of acceptance levels. Significance code: 0.01 '*' 0.05.

Dependent Variable		(I) Type	(J) Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Not in my back yard (A5)	Tukey HSD	Control Group	Information from the government	0.446	0.171	0.097	−0.04	0.93
			Information from the industry	0.217	0.182	0.842	−0.31	0.74
			Information from NGOs	0.414	0.186	0.229	−0.12	0.95
			Scientific Information	0.144	0.203	0.981	−0.44	0.73
			Information from scientists	0.508*	0.168	0.032	0.03	0.99
	Bonferroni	Control Group	Information from the government	0.446	0.171	0.141	−0.06	0.95
			Information from the industry	0.217	0.182	1.000	−0.32	0.76
			Information from NGOs	0.414	0.186	0.401	−0.14	0.96
			Scientific Information	0.144	0.203	1.000	−0.46	0.74
			Information from scientists	0.508*	0.168	0.040	0.01	1.00

that the homogeneity of variance assumption held asymptotically. The ANOVA result indicates a significant difference between the acceptance levels close to one's house among the control group and the group that received information from scientists was valid. The verified difference between the two groups implies that information of proper content from certain actors could help overcome the "not-in-my-back-yard" syndrome.

4.4. *Structural equation modeling (SEM) and the partial least squares (PLS) method*

Structural equation modeling (SEM) is a statistical technique that simultaneously estimates interdependent relationships between latent variables. Latent variables are not directly observed but inferred through their manifestations [74]. The latent variables (see Fig. 1) are perceived benefits, risks, and costs, procedural and distributive fairness, trust, outcome efficacy, problem perception, knowledge, experience, and acceptance. As a variance-based SEM method, PLS, which represents latent variables as a weighted composite score of their indicators, was used. This method places minimal restrictions on the sample size [75]. The nonparametric bootstrap method employed by PLS allows testing with smaller samples by randomly generating subsamples from the original data set. Furthermore, unlike the covariance-based SEM techniques, PLS does not result in negative variance estimates when the normality assumption is violated [75].

4.5. *Measurement model results*

The results for the control group presented in Fig. 2 and Table A.1 indicated that several items had loadings significantly lower than the accepted threshold of 0.7 [72,73]. However, it should be noted here that for more complex models 0.6 can be considered as the sufficient level [72].

Following this suggestion, the indicators "sufficiency of shale gas knowledge, transparency in planning, and political independence" were removed from the control group measurement model. Similarly, the following indicators were removed from the information group measurement model:

- Sufficiency of climate change knowledge
- Competence in assessment (regulators)
- Competence in assessment (operators)
- Ability to interfere when a problem arises (regulators)
- Ability to solve problems (operators)
- Seismic risk

The indicators:

- Disclosure of information about shale gas (regulators)
- Disclosure of information about shale gas (operators)
- Disclosure of information about alternatives to shale gas (regulators)
- Disclosure of information about alternatives to shale gas (operators)
- Scientific knowledge about risks
- Economic benefit
- Global warming as a concept against nature's laws

Were commonly removed from the constructs. The final loadings are presented in Table A.2.

4.6. *Scale reliability and validity for the control group*

Before testing hypotheses, the scale reliability and validity of each group were assessed. Reliability analysis scrutinizes the degree to which the measurement in a singular unidimensional construct is dependable [76]. According to the results presented in Table A.2, all modified constructs except one had a Cronbach's alpha value greater than the recommended minimum of 0.7 [77]. The alpha for problem perception was substantially below the minimum. As the loadings of the indicators were not significantly different, and no other indicator reflective of problem perception was identified, no changes were made to the construct.

All composite reliabilities were greater than 0.811, which is significantly above the recommended minimum of 0.707. Moreover, the average variance extracted (AVE) was evaluated to compare the amount of variance that a latent variable captures from its indicators to the variance that is an aftermath of measurement error [75]. Apart from the value for the more complex construct of trust, the AVEs for all constructs were at least 0.656, which is higher than the suggested minimum of 0.5 [73,75]. On the other hand, the value of AVE for trust was 0.476, which is still close to the suggested minimum. As trust was measured by several distinguishable items with comparable loadings, no modulations were made to the construct. Convergent validity was interpreted through an inspection of the square root of AVEs represented in the diagonal elements of Table 4. The results showed that apart from that for the trust factor, for which the value was 0.69 still close to the threshold, convergent validity values were all greater than 0.707. This corresponds to high internal consistency.

Finally, the discriminant validity of constructs was examined. In doing this analysis, the notion was to make sure that each construct shares more variance with their own measures than they share with the remaining constructs in the model [72]. The discriminant validity assessments were made by comparing the square root of AVEs given in the diagonal of Table 4, and the correlations of the latent variable with different constructs. Results suggested that all

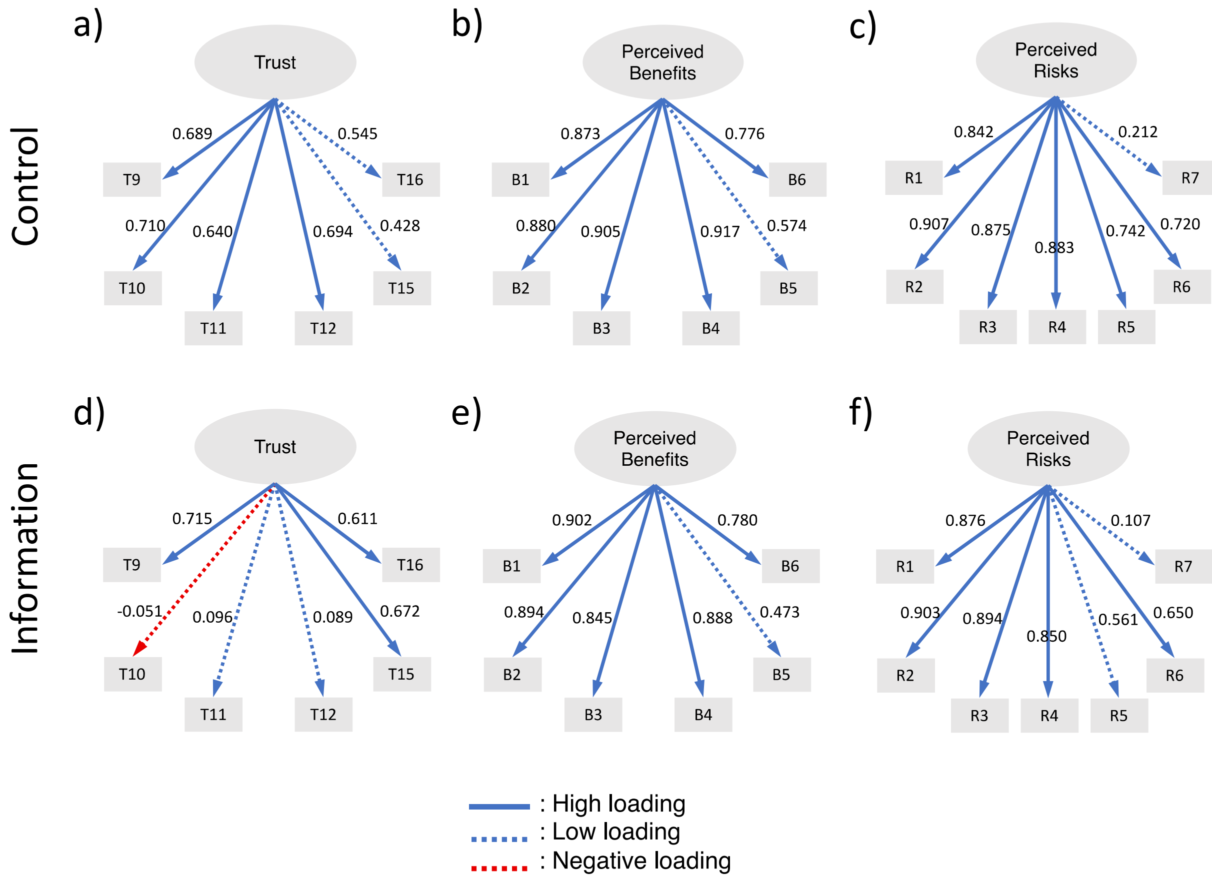

Fig. 2. Measurement model results: a) Trust, b) Perceived Benefits, c) Perceived Risks for the control group and d) Trust, e) Perceived Benefits and c) Perceived Risks for the information group. The rectangles represent observed variables, i.e., the response to each question in the survey, and the ellipses represent latent variables. A single-headed arrow portrays the nature of the construct (reflective or formative) and the number on each arrow designates the standardized regression coefficient. Please note that although T9 appears to have a high loading in this figure, upon removal of other items from the construct, its loading remained below the recommended minimum of 0.6. This figure is for comparison of the initial measurement model only.

Table 4
Discriminant validity and convergent validity of the constructs of the control group. Abbreviations are listed as follows: A: Acceptance, B: Perceived Benefits, C: Perceived Costs, DF: Distributive Fairness, E: Experience, K: Knowledge, OE: Outcome Efficacy, PF: Procedural Fairness, PP: Problem Perception, R: Perceived Risks, T: Trust.

	A	B	C	DF	E	K	OE	PF	PP	R	T
A	0.810										
B	0.704	0.877									
C	−0.030	0.056	1.000								
DF	0.320	0.251	−0.072	1.000							
E	0.007	0.033	0.064	−0.031	1.000						
K	0.034	0.098	−0.009	0.016	0.175	1.000					
OE	0.169	0.120	−0.017	0.236	−0.062	0.049	1.000				
PF	0.051	0.045	−0.046	0.168	0.043	0.083	0.405	1.000			
PP	−0.116	−0.052	−0.101	0.008	−0.108	−0.044	−0.188	−0.147	0.828		
R	−0.385	−0.279	0.399	−0.099	0.045	−0.048	0.006	0.065	0.019	0.831	
T	0.494	0.424	−0.066	0.448	−0.043	−0.033	0.384	0.277	−0.106	−0.239	0.690

square roots of AVEs were higher than the correlations between the focal construct and the remaining constructs [78]. Hence, the validity measures were quite acceptable.

4.7. Scale reliability and validity for the information group

In terms of scale reliability, all constructs in the information group except one had a Cronbach's alpha value greater than the recommended minimum of 0.7 (see Table A.2) [77]. The problem perception construct had an alpha of 0.487. Nevertheless, as the construct consisted of only two items, removing any item would resolve the issue with the low alpha value, so no changes were made to the construct. All composite reliabilities were greater than 0.792, which is above the recommended minimum of 0.707. Apart from the value for the more complex construct of trust, the AVEs for all constructs were at least 0.655, greater than the advised minimum [73,75]. For trust, the AVE value was found to be 0.477, which is acceptable given the complexity of the model being tested. For convergent validity, the results indicated that apart from that for the trust factor, for which the value (0.691) was still close to the threshold, convergent validity values were all greater than 0.707. A comparison of the square root of AVEs given in the diagonal of

Table 5, and the correlations of the latent variable with different constructs suggested that discriminant validity was attained, as well [78].

4.8. Structural model results

To test the significance of the paths in the structural model, the bootstrap resampling method was used. The resampling size was chosen as 500 [75]. A tabular representation of the initial model results can be found in Table A.1 and visual delineation of the structural model results upon removal of items with low loadings can be found in Fig. 3 and Table A.2.

The structural model results suggested that many of the hypothesized relationships were supported. Table B.1 and Fig. 3 represent the causal effects and their significance. The following were not confirmed in both the information and control group:

- The cultivation of knowledge is positively associated with the establishment of trust
- If more trust is placed in actors that have a role in shale gas development or in those responsible for supervising shale gas development, the perceived costs associated with the technology will decrease
- An increase in environmental problem perception is associated with an increase in the acceptance of shale gas development
- An increase in perceived costs is associated with a decrease in the social acceptance of shale gas development
- Outcome efficacy is positively associated with the acceptance of shale gas development

The following hypothesized relationships were confirmed for the control group but not for the information group:

- Experience is positively associated with knowledge
- Distributive fairness has a significant positive impact on the social acceptance of shale gas development

The predictive power of the models for the control and information groups was assessed by the explained variance (R^2) values of the endogenous constructs [73]. The literature on explained variance suggests that the values of 0.67, 0.33, and 0.19 represented a substantial, moderate, and weak fit, respectively [73]. Provided this, the results in Table 6 implied that the explanatory power for the endogenous variables ranged between the weak and moderate levels for the control group. For the end goal of acceptance, the model had satisfactory results. The analysis results indicated that 56% of the total variance of the acceptance of shale gas in the control group was attributed to trust, perceived risks, and benefits, experience, procedural and distributive fairness. The values were slightly different for the information group and highly satisfactory results were achieved for the acceptance construct. The analysis results indicated that 65% of the total variance of the acceptance of shale gas development in the information group was attributed to trust, perceived risks, perceived benefits, and procedural fairness. For model fit, the goodness-of-fit formula of Tenenhaus et al. was used [79]. This measure is derived upon taking the square root of the product of the average R^2 value of endogenous variables (i.e., acceptance, perceived benefits, risks and costs, knowledge, and trust) and the average AVE value. For the control group, the computed value was 0.342 (see Table 6). Unfortunately, this was slightly below the theoretical cut-off of 0.36 [78]. The goodness of fit value for the information group was 0.371 (see Table 6), which is above the cut-off [78].

To execute a robustness check, a multigroup analysis (MGA) was conducted with 5000 subsamples using a model which included indicators common to the reduced form model of both the information and control groups. The results in Table 7 revealed no significant differences among the path coefficients of both groups. Even though there were numerical differences in the inner relationships between factors that impact acceptance, information provision did not alter the relationships among psychological factors that impact the acceptance of shale gas development significantly. In other words, while information provision produced changes in the signs of the latent variables and influenced the extent to which they impacted attitudes to a certain degree, it did not necessarily produce significant differences in each factor's contribution to the formation of a stance towards shale gas development. As the mean knowledge values presented in Table 2 for the control (μcontrol = 3.46) and information groups (μinformation = 3.52) underline, participants did not consider themselves to be very knowledgeable about shale gas development even after having received information. The lack of sufficient knowledge about the technology could possibly explain why the inner relationships did not change substantially. It should however be noted here that exploring how the amount of information provided impacts attitude formation is not the intention of this research. This research rather focuses on the impact of the source and content of information in explaining attitudes towards the technology. Future research might explore whether the amount of information provided, and the frequency of communication may create meaningful differences in the inner relationships between factors that impact acceptance such that it results in significant changes in attitudes.

5. Discussion and policy implications

There are several takeaways for policymakers and researchers from both the measurement and structural model results that are

Table 5
Discriminant validity and convergent validity of the constructs of the information group. Abbreviations are listed as follows: A: Acceptance, B: Perceived Benefits, C: Perceived Costs, DF: Distributive Fairness, E: Experience, K: Knowledge, OE: Outcome Efficacy, PF: Procedural Fairness, PP: Problem Perception, R: Perceived Risks, T: Trust.

	A	B	C	DF	E	K	OE	PF	PP	R	T
A	0.809										
B	0.783	0.867									
C	−0.094	−0.073	1.000								
DF	0.290	0.287	−0.083	1.000							
E	−0.014	0.053	0.161	0.004	1.000						
K	0.025	0.038	0.076	0.129	0.006	1.000					
OE	0.050	0.107	0.104	0.144	−0.057	0.163	1.000				
PF	0.098	0.118	0.070	0.122	0.051	0.267	0.441	1.000			
PP	−0.103	−0.091	0.029	0.062	−0.039	0.006	0.020	0.049	0.811		
R	−0.548	−0.501	0.322	−0.186	0.043	0.100	0.097	0.032	0.015	0.843	
T	0.397	0.416	0.050	0.440	−0.037	0.093	0.306	0.423	0.053	−0.264	0.691

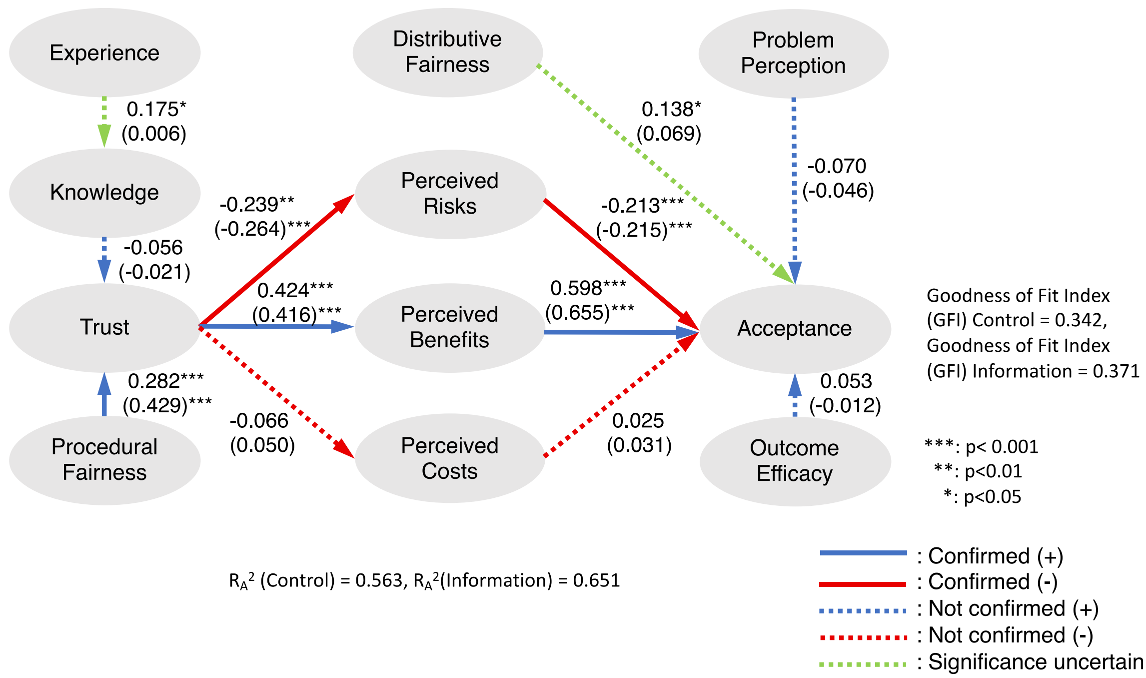

Fig. 3. Structural Model Results for Turkey. The numbers in parentheses represent the results for the information group. The colors of the single-headed arrows were determined based on control group results and are reflective of the hypothesized coefficients. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 6
R^2, communality, and goodness of fit.

	Acceptance	Perceived Benefits	Perceived Costs	Knowledge	Perceived Risks	Trust	Average
R^2 (Control Group)	0.563	0.180	0.004	0.031	0.057	0.080	0.153
R^2 (Information Group)	0.651	0.173	0.002	0.000	0.070	0.180	0.179
Communality (AVE) (Control Group)	0.656	0.769	1.000	1.000	0.691	0.476	0.765
Communality (AVE) (Information Group)	0.655	0.751	1.000	1.000	0.711	0.477	0.766
Goodness of Fit (Control Group)	0.342						
Goodness of Fit (Information Group)	0.371						

Table 7
PLS MGA structural estimate differences.

	Impact	Path Coefficient Difference (|Control-Information|)	p-value (Control vs Information)	Significance
H1	Experience → Knowledge	0.055	0.726	No
H2	Knowledge → Trust	0.099	0.825	No
H3	Procedural Fairness → Trust	0.101	0.847	No
H4	Trust → Perceived Risks	0.034	0.384	No
H5	Trust → Perceived Benefits	0.040	0.317	No
H6	Trust → Perceived Costs	0.097	0.801	No
H7	Problem Perception → Acceptance	0.024	0.642	No
H8	Perceived Risks → Acceptance	0.007	0.533	No
H9	Perceived Benefits → Acceptance	0.062	0.779	No
H10	Perceived Costs → Acceptance	0.003	0.520	No
H11	Distributive Fairness → Acceptance	0.072	0.163	No
H12	Outcome Efficacy → Acceptance	0.065	0.164	No

discussed in the following sub-sections.

5.1. Measurement model discussion

The first important result was that information provision could address some major concerns of the public. Seismic risk was not an important factor when individuals were provided with information. This suggests that the high factor loading for the control group may be representative of the development of attitudes based on intuitive feelings. Given that the Thrace Basin in Turkey, where a significant portion of the shale resources is found, is a region deformed by the North Anatolian fault system [80], the survey respondents may have been anxious about induced seismicity events. Nevertheless, respondents in the information group were relieved, likely because they developed a better understanding of the technology. This finding is closely aligned with the results of studies in the U.K. [32,33,35], suggesting that policymakers should be cognizant of the dynamic nature of social acceptance, educate people about the potential risks and benefits associated with resource development and continuously monitor how the acceptance measures in our model change. It is also critical to understand acceptance in countries with similar geological characteristics. The Marcellus play in the U.S., for instance, is surrounded by northeast-trending folds in the Valley and Ridge province [81,82]. Information provision could be key to building trust and reducing risk perception in this region.

Second, individuals who became more knowledgeable desired more transparency. This was confirmed numerically by tracing the loadings of the "transparency" indicator for the control and information groups. The low loading for the control group compared to the high loading in the information group (Table A.2) suggests that as exposure to information increases, communities may be disturbed by not being informed about the decision-making process. Prior research underlined the importance of this factor [5,53]. However, it had not traced changes in the significance of transparency as the technology and its potential impacts became part of the public discourse. This could be an interesting point for future research. Comparing the relative importance of the transparency indicator in regions or other countries where shale gas development is already taking place could make a valuable contribution. Overall, the major policy implication would be that authorities should explore effective communication options with the public at the very early stages of the technology's adoption so that information disclosure does not constitute a barrier at the later stages of project implementation.

The final result was the low item loading of "economic benefit" for both the information and control group (see Table A.2). Given that previous research in the U.S. concluded that mineral rights ownership is associated with the public perception of the natural gas industry [28,30], it is likely that this result is peculiar to Turkey or other civil law countries that have similar mineral rights ownership structures. In Turkey, the economic benefits derived from resource development do not directly transfer to the individual landowners. The state exclusively and imprescriptibly owns the mineral rights [83]. While mineral rights owners in the United States have obtained substantial gains from royalty payments [39], individuals in Turkey do not feel that there would be any economic benefit associated with the development. Hence, policymakers should recognize the spatial differences in economic motives and reflect on how these differences may impact the way individuals form opinions on energy technologies before they develop business models for different countries.

5.2. Structural model discussion

The first important result of the structural model assessment was that environmental problem perception did not have a significant direct effect on the acceptance of shale gas development. In other words, the extent to which individuals felt that climate change constituted a threat did not impact their attitudes towards shale gas development significantly. This is an interesting finding, particularly because environmental problem perception had previously been identified as an important factor in explaining attitudes towards renewable energy development [20,46,47,61]. In designing the theoretical framework, we had hypothesized that individuals who were more concerned about the prevention of global warming would favor a technology that reduces CO_2 emissions, whether this is a cleaner fossil fuel resource or a renewable energy source. However, not only did we find the factor of problem perception to be unimportant in explaining attitudes towards shale gas development, but we also discerned that the environmental interference perception for global warming exerted a negative influence on the social acceptance of shale gas development. This is where we believe fossil fuel acceptance models may differ from renewable energy technology acceptance models. Our analysis prompts us to believe that individuals do not associate shale gas development with a reduction of greenhouse gas emissions, an observation that has indeed been made in the U.K [33–35]. Not having made this association, a citizen concerned about humanity's impact on the environment, becomes more supportive of renewable energy technologies rather than shale gas development, which is perceived as a dirty energy source (hence the negative association). Therefore, emphasizing the idea that shale gas has a cleaner environmental footprint will only be marginally beneficial. Instead, focusing efforts on addressing the technology-specific risks by setting stricter restrictions on flaring, supporting research efforts on wastewater disposal, or establishing a more equal distribution of benefits could influence attitudes more substantially.

The second important result was that while the experience factor was a direct determinant of knowledge for the control group, it was not a significant factor that explained acceptance for the information group. This suggests that when individuals are provided with information, they tend to rely on the knowledge acquired through that excerpt. When there is no such information though, experience may come into play. This is important for policy design because it underlines that selecting an adequate means of communication between members of the public and key stakeholders could prevent previous experiences from becoming a detriment. Particularly, in regions where previous natural disaster experiences unrelated to shale gas development may shape opinions, policymakers should try to engage stakeholders as early as possible and disseminate information about the risks and benefits associated with the technology. This will ensure that individuals use factual information in arriving at a judgment and that they bring up more legitimate concerns.

The third important result relates to the perceived costs factor. The analysis showed that the hypothesized relationship between trust and perceived costs, and perceived costs and acceptance were both insignificant. Hence, the cost factor was revisited. One may claim that individuals either do not place importance on financial factors that they are not knowledgeable about or they do not believe financial factors impact them significantly. This is in line with our finding that economic benefit is not an important factor. This is most likely because they do not realize the extent to which development costs influence the prices that consumers face. If that is the case, then the shale gas discourse should focus on aspects that individuals are more familiar with and that have a more direct impact on local communities. These aspects could include issues such as water contamination and induced seismicity, which have been identified as relevant factors in explaining attitudes towards shale gas development [33–35].

6. Conclusions

There are at least three high-level benefits of the integration of social acceptance into energy resource policy discussions. First, it serves to get the science of societal risk evaluation right. Analytical models based on a set of simple assumptions such as the rational economic choice model with complete information have been criticized for not incorporating conclusions derived from empirical analysis of real-world phenomena into their structure. Although they are highly attractive from an intellectual standpoint, they remain unlikely to provide the level of understanding necessary to transition to sustainable systems within desired time frames. Moreover, while empirical models have been utilized broadly to study the societal impacts of oil and gas development, no single approach or group of metrics has emerged as best practice. The underlying reasons for this include the fact that the evidence utilized in analysis comes from various sources including but not limited to local knowledge, scientific research, or a combination of the two, and that problems and interventions are context-specific. For this reason, key actors involved in decision-making processes have not been able to develop a common understanding of the current situation and key areas of improvement. On the other hand, the method employed in this research may provide a universal tool for population assessments and screening the relative impact various factors have on the opinions, evaluations, and behavioral intentions of the public.

Second, the framework employed here provides an opportunity to scale up localized solutions. Many sustainable solutions depend on very specific aspects of their ecosystems. For instance, differences in geological characteristics, regulatory environment, and market structure, and technical aspects require most of the interventions to be individualized. While research has been successful in identifying key barriers and opportunities on a case-by-case basis, empirical assessments of human interactions with environmental systems have not yielded universal laws. The model in this paper is promising in that it could apply to several different social and spatial contexts. Even though the analysis results would vary by country or region, the indicator development process used in this paper could be followed to evaluate the social acceptance of different resource extraction projects. Once the sensitivities of multiple communities are better understood, policymakers could compare these responses to identify the common traits and differences. To that end, we recommend targeting research at more locations to ensure that decision-makers focus on aspects that may achieve the greatest impact.

Third, this approach could be utilized for the continual improvement of policy designs. Developing practices that are responsive to public values, interests, and concerns through time is critical to developing sustainable solutions. This requires the metric to be a longitudinal measure, rather than an instantaneous measure of an attribute that may not be relevant in the future. Models that are based on psychological theories, can easily be used for adaptive management of natural resource policy. As technological and scientific advancements continue to inform decision-makers, they may identify novel indicators that are relevant to public acceptance and easily integrate them into the model while preserving the core latent construct structure.

Credit author statement

Dilge Kanoglu: Conceptualization, Methodology, survey design, Software, Validation, Formal analysis, Investigation, Data curation, writing, editing, Visualization. Ugur Soytas: Conceptualization, Supervision, survey design, Investigation, writing, review and editing.

Declaration of competing interest

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

Appendix A

Table A.1
Measurement properties of the initial constructs

Construct	Item Indicator (Control Group)	Item Loading (Control Group)	Item Loading (Information Group)	T Statistics (Control Group)	T Statistics (Information Group)	Cronbach's Alpha (Control Group)	Cronbach's Alpha (Information Group)	Composite Reliability (Control Group)	Composite Reliability (Information Group)	Communality (AVE) (Control Group)	Communality (AVE) (Information Group)
Experience						1.000	1.000	1.000	1.000	1.000	1.000
	E1	1.000	1.000	0.000	0.000						
Knowledge						0.500	0.511	0.497	0.741	0.465	0.612
	K1	0.962	0.507	2.790	1.249						
	K2	0.065	0.984	0.164	3.056						
Trust						0.826	0.838	0.841	0.850	0.323	0.308
	T1	0.688	0.654	14.850	13.361						
	T2	0.746	0.508	21.755	16.834						
	T3	−0.135	0.565	0.935	0.398						
	T4	−0.054	0.523	0.372	0.740						
	T5	−0.071	0.712	0.515	0.675						
	T6	0.064	0.722	0.570	1.397						
	T7	0.660	0.658	13.146	12.528						
	T8	0.621	0.600	12.855	13.089						
	T9	0.689	0.715	15.712	9.122						
	T10	0.710	−0.051	14.489	6.315						
	T11	0.640	0.096	11.270	7.464						
	T12	0.694	0.089	15.756	6.644						
	T13	0.739	0.175	18.224	16.282						
	T14	0.618	0.665	11.271	16.891						
	T15	0.428	0.672	5.373	12.367						
	T16	0.545	0.611	9.211	10.876						
Perceived Risks						0.874	0.841	0.905	0.882	0.599	0.551
	R1	0.842	0.876	26.321	42.462						
	R2	0.907	0.903	50.795	54.003						
	R3	0.875	0.894	40.631	52.150						
	R4	0.883	0.850	46.424	32.328						
	R5	0.742	0.561	13.753	6.515						
	R6	0.720	0.650	12.866	10.892						
	R7	0.212	0.107	1.871	0.956						

Table A.1 (*continued*)

Construct	Item Indicator (Control Group)	Item Loading (Control Group)	Item Loading (Information Group)	T Statistics (Control Group)	T Statistics (Information Group)	Cronbach's Alpha (Control Group)	Cronbach's Alpha (Information Group)	Composite Reliability (Control Group)	Composite Reliability (Information Group)	Communality (AVE) (Control Group)	Communality (AVE) (Information Group)
Perceived Benefits						0.905	0.888	0.928	0.918	0.688	0.658
	B1	0.873	0.902	42.972	46.474						
	B2	0.880	0.894	38.752	45.383						
	B3	0.905	0.845	61.668	30.988						
	B4	0.917	0.888	64.172	49.425						
	B5	0.574	0.473	9.574	6.802						
	B6	0.776	0.780	20.873	22.386						
Perceived Costs						1.000	1.000	1.000	1.000	1.000	1.000
	C1	1.000	1.000	0.000	0.000						
Procedural Fairness						1.000	1.000	1.000	1.000	1.000	1.000
	PF1	1.000	1.000	0.000	0.000						
Distributive Fairness						1.000	1.000	1.000	1.000	1.000	1.000
	DF1	1.000	1.000	0.000	0.000						
Problem Perception						0.589	0.437	0.461	0.413	0.362	0.373
	PP1	0.849	0.695	2.051	1.726						
	PP2	−0.155	−0.287	0.328	0.568						
	PP3	0.584	0.744	2.037	1.719						
Outcome Efficacy						1.000	1.000	1.000	1.000	1.000	1.000
	OE1	1.000	1.000	0.000	0.000						
Acceptance						0.867	0.865	0.905	0.904	0.656	0.655
	A1	0.875	0.852	43.541	29.920						
	A2	0.809	0.888	23.117	41.166						
	A3	0.878	0.872	47.714	41.076						
	A4	0.755	0.758	22.463	16.893						
	A5	0.721	0.652	18.339	12.694						

Table A.2
Measurement properties of the final constructs.

Construct	Item Indicator (Control Group)	Item Loading (Control Group)	Item Loading (Information Group)	T Statistics (Control Group)	T Statistics (Information Group)	Cronbach's Alpha (Control Group)	Cronbach's Alpha (Information Group)	Composite Reliability (Control Group)	Composite Reliability (Information Group)	Communality (AVE) (Control Group)	Communality (AVE) (Information Group)
Experience						1.000	1.000	1.000	1.000	1.000	1.000
	E1	1.000	1.000	0.000	0.000						
Knowledge						1.000	1.000	1.000	1.000	1.000	1.000
	K1	1.000									
	K2		1.000	0.000	0.000						
Trust						0.878	0.844	0.900	0.879	0.476	0.477
	T1	0.698	0.715	14.955	17.151						
	T2	0.758	0.764	21.869	22.170						
	T3										
	T4										
	T5										
	T6										
	T7	0.665	0.677	12.540	15.992						
	T8	0.630	0.680	12.695	15.098						
	T9	0.698		16.170							
	T10	0.734		17.410							
	T11	0.651		11.899							
	T12	0.713		17.343							
	T13	0.726	0.669	19.208	13.942						
	T14	0.611	0.687	11.717	14.344						
	T15		0.692		15.064						
	T16		0.634		11.997						
Perceived Risks						0.909	0.894	0.930	0.924	0.691	0.711
	R1	0.842	0.876	25.939	43.052						
	R2	0.906	0.912	49.901	51.180						
	R3	0.874	0.901	42.526	55.148						
	R4	0.884	0.852	46.971	33.852						
	R5	0.742		14.408							
	R6	0.721	0.645	12.904	11.249						
	R7										
Perceived Benefits						0.924	0.916	0.943	0.938	0.769	0.751
	B1	0.871	0.909	39.108	47.779						

(*continued on next page*)

Table A.2 (*continued*)

Construct	Item Indicator (Control Group)	Item Loading (Control Group)	Item Loading (Information Group)	T Statistics (Control Group)	T Statistics (Information Group)	Cronbach's Alpha (Control Group)	Cronbach's Alpha (Information Group)	Composite Reliability (Control Group)	Composite Reliability (Information Group)	Communality (AVE) (Control Group)	Communality (AVE) (Information Group)
	B2	0.889	0.888	42.866	41.375						
	B3	0.921	0.858	67.942	32.155						
	B4	0.927	0.894	74.702	51.735						
	B5										
	B6	0.769	0.777	21.851	22.620						
Perceived Costs						1.000	1.000	1.000	1.000	1.000	1.000
	C1	1.000	1.000	0.000	0.000						
Procedural Fairness						1.000	1.000	1.000	1.000	1.000	1.000
	PF1	1.000	1.000	0.000	0.000						
Distributive Fairness						1.000	1.000	1.000	1.000	1.000	1.000
	DF1	1.000	1.000	0.000	0.000						
Problem Perception						0.567	0.487	0.811	0.792	0.685	0.657
	PP1	0.922	0.750	4.095	2.258						
	PP2										
	PP3	0.721	0.868	2.484	2.872						
Outcome Efficacy						1.000	1.000	1.000	1.000	1.000	1.000
	OE1	1.000	1.000	0.000	0.000						
Acceptance						0.867	0.865	0.905	0.904	0.656	0.655
	A1	0.873	0.852	40.347	29.967						
	A2	0.808	0.888	22.857	37.926						
	A3	0.879	0.871	49.034	39.702						
	A4	0.756	0.758	21.958	17.267						
	A5	0.722	0.653	16.203	13.069						

Appendix B

Table B.1
Structural estimates with hypothesized relationships. Abbreviations are listed as follows: E: Experience, K: Knowledge, T: Trust, PF: Procedural Fairness, R: Perceived Risks, B: Perceived Benefits, C: Perceived Costs, PP: Problem Perception, A: Acceptance, DF: Distributive Fairness, OE: Outcome Efficacy.

		Direct Effect (Control Group)	Direct Effect (Information Group)	T Statistics (Control Group)	T Statistics (Information Group)	P Values (Control Group)	P Values (Information Group)	Hypothesis Supported? (Control Group)	Hypothesis Supported? (Information Group)
H1	E → K	0.175	0.006	2.499	0.094	0.013	0.925	Yes (5% level)	No
H2	K → T	−0.056	−0.021	0.776	0.307	0.438	0.759	No	No
H3	PF → T	0.282	0.429	4.177	7.249	0.000	0.000	Yes (0.1% level)	Yes (0.1% level)
H4	T → R	−0.239	−0.264	2.865	3.677	0.004	0.000	Yes (1% level)	Yes (0.1% level)
H5	T → B	0.424	0.416	6.190	6.951	0.000	0.000	Yes (0.1% level)	Yes (0.1% level)
H6	T → C	−0.066	0.050	0.804	0.617	0.422	0.537	No	No
H7	PP → A	−0.070	−0.046	1.156	0.900	0.248	0.369	No	No
H8	R → A	−0.213	−0.215	3.371	4.230	0.001	0.000	Yes (1% level)	Yes (1% level)
H9	B → A	0.598	0.655	9.294	13.034	0.000	0.000	Yes (0.1% level)	Yes (0.1% level)
H10	C → A	0.025	0.031	0.500	0.786	0.617	0.432	No	No
H11	DF → A	0.138	0.069	2.261	1.687	0.024	0.092	Yes (5% level)	No
H12	OE → A	0.053	−0.012	1.118	0.294	0.264	0.769	No	No

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2021.122150.

References

[1] Pidgeon N, Demski CC. From nuclear to renewable: energy system transformation and public attitudes. Bull At Sci 2012;68(4):41–51.
[2] Papadis E, Tsatsaronis G. Challenges in the decarbonization of the energy sector. Energy 2020;205.
[3] Raven RP, Mourik RM, Feenstra CFJ, Heiskanen E. Modulating societal acceptance in new energy projects: towards a toolkit methodology for project managers. Energy 2009;34(5):564–74.
[4] Savvanidou E, Zervas E, Tsagarakis KP. "Public acceptance of biofuels," Energy Policy 2010;37(7):3482–8.
[5] Musall FD, Kuik O. "Local acceptance of renewable energy—a case study from southeast Germany. Energy Pol 2011;39(6):3252–60.
[6] Bhowmik C, Bhowmik S, Rayb A. Social acceptance of green energy determinants using principal component analysis. Energy 2018;160:1030–46.
[7] Bertsch V, Hall M, Weinhardt C, Fichtner W. Public acceptance and preferences related to renewable energy and grid expansion policy: empirical insights for Germany. Energy 2016;114:465–77.
[8] Montijn-Dorgelo FN, Midden CJ. The role of negative associations and trust in risk perception of new hydrogen systems. J Risk Res 2008;11(5):659–71.
[9] Midden CJ, Huijts N. The role of trust in the affective evaluation of novel risks: the case of co2 storage. Risk Anal 2009;29(5):743–51.
[10] Bronfman NC, Jiménez RB, Arévalo PC, Cifuentes LA. Understanding social acceptance of electricity generation sources. Energy Pol 2012;46:246–52.
[11] Visschers VHM, Siegrist M. Fair play in energy policy decisions: procedural fairness, outcome fairness and acceptance of the decision to rebuild nuclear power plants. Energy Pol 2012;46:292–300.
[12] Ladenburg J. Attitudes towards on-land and offshore wind power development in Denmark; choice of development strategy. Renew Energy 2008;33(1):111–8.
[13] Kânoğlu D, Soytaş U. The impact of information provision on the social acceptance of shale gas development: a review-based inclusive model. Frontiers in Energy Research 2018;6(83).
[14] H. Boudet, C. Clarke, D. Bugden, E. Maibach, C. Roser-Renouf, and A. Leiserowitz, "'Fracking' controversy and communication: using national survey data

to understand public perceptions of hydraulic fracturing," Energy Pol, vol. 65, pp. 57–67, Feb. 2014, doi: 10.1016/j.enpol.2013.10.017.
[15] Andersson-Hudson J, Knight W, Humphrey M, O'Hara S. Exploring support for shale gas extraction in the United Kingdom. Energy Pol 2016;98:582–9.
[16] Brasier KJ, McLaughlin DK, Rhubart D, Stedman RC, Filteau MR, Jacquet J. Risk perceptions of natural gas development in the marcellus shale. Environ Pract 2013;15(2):108–22.
[17] Ferrar KJ, Kriesky J, Christen CL, Marshall LP, Malone SL, Sharma RK, Michanowicz DR, Goldstein BD. Assessment and longitudinal analysis of health impacts and stressors perceived to result from unconventional shale gas development in the marcellus shale region. Int J Occup Environ Health 2013;19(2):104–12.
[18] Schafft KA, Borlu Y, Glenna L. The relationship between marcellus shale gas development in Pennsylvania and local perceptions of risk and opportunity. Rural Sociol 2013;78(2):143–66.
[19] Krause RM, Carley SR, Warren DC, Rupp JA, Graham JD. "'Not in (or under) my backyard': geographic proximity and public acceptance of carbon capture and storage facilities. Risk Anal 2014;34(3):529–40. https://doi.org/10.1111/risa.12119.
[20] Y. Guo, P. Ru, J. Su, and L. D. Anadon, "Not in my backyard, but not far away from me: local acceptance of wind power in China," Energy, vol. 82, pp. 722–733, Mar. 2015, doi: 10.1016/j.energy.2015.01.082.
[21] Wolsink M. Invalid theory impedes our understanding: a critique on the persistence of the language of NIMBY Trans Inst Br Geogr NS 2006;31:85–91.
[22] C. R. Warren, C. Lumsden, S. O'Dowd, and R.V. Birnie,"'Green on green': public perceptions of wind power in Scotland and Ireland," J Environ Plann Manag, vol. 48, no. 6, pp. 853–875, Nov. 2005, doi: 10.1080/09640560500294376.
[23] B. Williams, "The YIMBY phenomenon in henoko, okinawa: compensation politics and grassroots democracy in a base community," Asian Surv, vol. 53, no. 5. pp. 958–978, Sep. 2013, doi: 10.1525/AS.2013.53.5.958.
[24] Devine-Wright P. Beyond NIMBYism: towards an integrated framework for understanding public perceptions of wind energy. Wind Energy Apr. 2005;8(2):125–39. https://doi.org/10.1002/we.124.
[25] Wolsink M. Wind power and the NIMBY-myth: institutional capacity and the limited significance of public support. Renew Energy 2000;21:49–64 [Online]. Available: www.elsevier.com/locate/renene.
[26] J. B. Jacquet, "Landowner attitudes toward natural gas and wind farm development in northern Pennsylvania," Energy Pol, vol. 50, pp. 677–688, Nov. 2012, doi: 10.1016/j.enpol.2012.08.011.
[27] Boudet H, Bugden D, Zanocco C, Maibach E. "The effect of industry activities on public support for 'fracking. Environ Pol Jul. 2016;25(4):593–612. https://doi.org/10.1080/09644016.2016.1153771.
[28] Theodori GL. Public perception of the natural gas industry: data from the Barnett Shale. Energy Sources B Energy Econ Plann Dec. 07, 2012;7(3):275–81. https://doi.org/10.1080/15567240903030562.
[29] Kriesky J, Goldstein BD, Zell K, Beach S. Differing opinions about natural gas drilling in two adjacent counties with different levels of drilling activity. Energy Pol Jul. 2013;58:228–36. https://doi.org/10.1016/j.enpol.2013.03.005.
[30] Boudet HS, Zanocco CM, Howe PD, Clarke CE. The effect of geographic proximity to unconventional oil and gas development on public support for hydraulic fracturing. Risk Anal 2018;38(9):1871–90. https://doi.org/10.1111/risa.12989.
[31] Stedman RC, Jacquet JB, Filteau MR, Willits FK, Brasier KJ, McLaughlin DK. Environmental reviews and case studies: marcellus shale gas development and new boomtown research: views of New York and Pennsylvania residents. Environ Pract Dec. 2012;14(4):382–93. https://doi.org/10.1017/S1466046612000403.
[32] Whitmarsh L, Nash N, Upham P, Lloyd A, Verdon JP, Kendall JM. UK public perceptions of shale gas hydraulic fracturing: the role of audience, message and contextual factors on risk perceptions and policy support. Appl Energy 2015;160:419–30.
[33] O'Hara S, Humphrey M, Jaspal R, Nerlich B, Poberezhskaya M. "Public perception of shale gas extraction in the UK: how people's views are changing. " University of Nottingham; 2013.
[34] O'Hara S, Humphrey M, Andersson-Hudson J, Knight W. Public perception of shale gas extraction in the UK: two years on from the Balcombe protests. " University of Nottingham; 2015.
[35] O'Hara S, Humphrey M, Andersson-Hudson J, Knight W. Public perception of shale gas extraction in the UK: from positive to negative. " University of Nottingham; 2017.
[36] H. Tan, Huimin, G. Wong-Parodi, and J. Xu. "Not under my backyard? Psychological distance, local acceptance, and shale gas development in China," Energy Research & Social Science 61, 2020.
[37] Ajzen I. The theory of planned behavior. Organ Behav Hum Decis Process 1991;50(2):179–211.
[38] Tokushige K, Akimoto K, Tomoda T. Public acceptance and risk- benefit perception of co2 geological storage for global warming mitigation in Japan. Mitig Adapt Strategies Glob Change 2007;12(7):1237–51.
[39] Small MJ, Stern PC, Bomberg E, Christopherson SM, Goldstein BD, Israel AL, Jackson RB, Krupnick A, Mauter MS, Nash J, et al. Risks and risk governance in unconventional shale gas development. 2014.
[40] Sovacool BK. Cornucopia or curse? reviewing the costs and benefits of shale gas hydraulic fracturing (fracking). Renew Sustain Energy Rev 2014;37:249–64.
[41] Slovic P, Fischoff B, Lichtenstein S. In: Hohenemser C, Kasperson JX, editors. "Managing the hazards of technology," perilous progress. Kates RW; 1985. p. 91–125. Boulder, CO, Westview.
[42] Schwartz SH, Howard JA. "A normative decision-making model of altruism," Altruism and Helping Behavior. 1981. p. 189–211.
[43] Schwartz SH. Normative influences on altruism. In advances in experimental social psychology, vol. 10. Elsevier; 1977. p. 221–79.
[44] Huijts NM, Midden CJ, Meijnders AL. Social acceptance of carbon dioxide storage. Energy Pol 2007;35(5):2780–9.
[45] Tokushige K, Akimoto K, Tomoda T. Public perceptions on the acceptance of geological storage of carbon dioxide and information influencing the acceptance. International Journal of Greenhouse Gas Control 2007;1(1):101–12.
[46] Steg L, Groot J. Explaining prosocial intentions: testing causal relationships in the norm activation model. Br J Soc Psychol 2010;49(4):725–43.
[47] Lindenberg S, Steg L. Normative, gain and hedonic goal frames guiding environmental behavior. J Soc Issues 2007;63(1):117–37.
[48] Peters E, Slovic P. The role of affect and worldviews as orienting dispositions in the perception and acceptance of nuclear power. J Appl Soc Psychol 1996;26(16):1427–53.
[49] Fox J. "Gasland: a film by josh fox," International WOW Co. Milanville, PA.(1:00: 56). See also, Energy in Depth. Debunking gasland. Dated june, vol. 9; 2010. p. 2010. 2010.
[50] Rousseau DM, Sitkin SB, Burt RS, Camerer C. Not so different after all: a cross-discipline view of trust. Acad Manag Rev 1998;23(3):393–404.
[51] Terwel BW, Harinck F, Ellemers N, Daamen DD. Competence-based and integrity-based trust as predictors of acceptance of carbon dioxide capture and storage (ccs). Risk Anal 2009;29(8):1129–40.
[52] Johnson BB. Exploring dimensionality in the origins of hazard-related trust. J Risk Res 1999;2(4):325–54.
[53] Peters RG, Covello VT, McCallum DB. The determinants of trust and credibility in environmental risk communication: an empirical study. Risk Anal 1997;17(1):43–54.
[54] Frewer LJ, Howard C, Hedderley D, Shepherd R. What determines trust in information about food-related risks? underlying psychological constructs. Risk Anal 1996;16(4):473–86.
[55] Schuitema G, Steg L, Van Kruining M. When are transport pricing policies fair and acceptable? Soc Justice Res 2011;24(1):66–84.
[56] Gross C. Community perspectives of wind energy in Australia: the application of a justice and community fairness framework to increase social acceptance. Energy Pol 2007;35(5):2727–36.
[57] Earle TC, Siegrist M. On the relation between trust and fairness in environmental risk management. Risk Anal 2008;28(5):1395–414.
[58] Lind EA, Van den Bos K. When fairness works: toward a general theory of uncertainty management. Res Organ Behav 2002;24:181–223.
[59] Visschers VH, Siegrist M. How a nuclear power plant accident influences acceptance of nuclear power: results of a longitudinal study before and after the fukushima disaster. Risk Anal 2013;33(2):333–47.
[60] De Best-Waldhober M, Daamen D. Public perceptions and preferences regarding large scale implementation of six co2 capture and storage technologies. well-informed and well-considered opinions versus uninformed pseudo-opinions of the Dutch public. The Netherlands.: " Centre for Energy and Environmental Studies, Faculty of Social Sciences, Leiden University and Copernicus Institute, Utrecht University; 2006.
[61] Huijts NM, Molin EJ, Steg L. Psychological factors influencing sustainable energy technology acceptance: a review-based comprehensive framework. Renew Sustain Energy Rev 2012;16(1):525–31.
[62] Wang S, Wang S, Lin S, Lia J. How and when does information publicity affect public acceptance of nuclear energy? Energy 2020;198:117290.
[63] Kok M, Merey S. Shale gas: current perspectives and future prospects in Turkey and the world. Energy Sources, Part A Recovery, Util Environ Eff 2014;36(22):2492–501.
[64] EIA U. Technically recoverable shale oil and shale gas resources, vol. 10. " Retrieved September; 2013. 2013.
[65] Calder BJ, Phillips LW, Tybout AM. Designing research for application. J Consum Res 1981;8:197–207.
[66] Greenberg J. The college sophomore as Guinea pig: setting the record straight. Acad Manag Rev 1987;12:157–9.
[67] Brown SP, Stayman DM. Antecedents and consequences of attitude toward the ad: a meta-analysis. J Consum Res 1992;19:34–51.
[68] Peterson RA. On the use of college students in social science research: insights from a second-order meta-analysis. J Consum Res 2001;28(3):450–61.
[69] Mullinix KJ, Leeper TJ, Druckman JN, Freese J. The generalizability of survey experiments. Journal of Experimental Political Science 2015;2(2):109–38.
[70] Beltramini RF. Student surrogates in consumer research. J Acad Market Sci 1983;11(4):438–43.
[71] Dul J, Hak T. Case study methodology in business research. Routledge; 2007.
[72] Hulland J. Use of partial least squares (pls) in strategic management research: a review of four recent studies. Strat Manag J 1999;20(2):195–204.
[73] Peng DX, Lai F. Using partial least squares in operations management research: a practical guideline and summary of past research. J Oper Manag 2012;30(6):467–80.
[74] Bowen NK, Guo S. Structural equation modeling. Oxford University Press; 2011.
[75] Chin WW. The partial least squares approach to structural equation modeling. Modern Methods for Business Research 1998;295(2):295–336.
[76] Sekaran U, Bougie R. Research methods for business: a skill building approach.

John Wiley & Sons; 2016.
[77] Nunnally J, Bernstein I. Psychometric theory. New York: " McGraw-Hill; 1978.
[78] Fornell C, Larcker DF. Structural equation models with unobservable variables and measurement error: algebra and statistics. J Market Res 1981:382−8.
[79] Tenenhaus M, Vinzi VE, Chatelin Y-M, Lauro C. Pls path modeling. Comput Stat Data Anal 2005;48(1):159−205.
[80] Cavazza W, Caracciolo L, Critelli S, d'Atri A, Zuffa GG. Petrostratigraphic evolution of the Thrace Basin (Bulgaria, Greece, Turkey) within the context of Eocene-Oligocene post-collisional evolution of the Vardar-Izmir-Ankara suture zone. Geodin Acta 2013;26(1−2):12−26.
[81] Harper JA, Laughrey CD. "Geology of oil and gas fields of southwestern Pennsylvania," Mineral Resource Report, vol. 4. Harrisburg, PA: Pennsylvania Geological Survey publication; 1987. p. 148−66.
[82] Harper JA. The Geology of Pennsylvania 1999;7:108−27.
[83] Budak SA. Mining − Turkey. The Law Reviews; 2016. https://thelawreviews.co.uk/edition/the-mining-law-review-edition-5/1140365/mining-turkey.