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Impact on the perceived landscape quality through renewable energy infrastructure. A discrete choice experiment in the context of the Swiss energy transition

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ABSTRACT

This paper examines how mixes (wind, photovoltaic, power lines) of different renewable energy infrastructure (REI) impact people's preferences for various landscape types. This does not only involve the visual character but also meanings that are assigned to these landscapes, which together influence the perceived landscape quality. The research is based on a representative online panel survey of Swiss residents (n = 1062). A discrete choice model (15 choice tasks) was implemented to estimate people's preferences for different REI scenarios across several landscape types. Hierarchical Bayes analysis allowed us to determine preferences of the different respondents, while choice simulation allowed us to estimate preferences for every potential scenario (n = 224) of the discrete choice experiment. While the results show a heterogeneous picture of people's preferences, they also reveal common general patterns. Near-natural, mid/high-elevation landscapes in the Alps are clearly rejected for REI implementation. Landscapes dominated by settlements or intensive agricultural use and landscapes in mountain tourist areas are preferably selected for REI developments. REI scenarios including overhead power lines perform consistently lower than scenarios without power lines. Overall, high preferences for scenarios with low REI indicate that society still lacks awareness of the need for massive REI implementation to achieve a sustainable energy transition.

1. Introduction

As a consequence of climate change mitigation strategies and related unsolved environmental issues, many countries are confronted with an energy shortfall due to the planned phaseout of fossil and nuclear power plants. To cover the substantial gaps in energy production and to push the energy system towards a sustainable development, many energy strategies focus on the development of new renewable energy sources like photovoltaic and wind infrastructure or biomass (and others). In Switzerland, for example, the gap in energy production is estimated to amount to ca. 24.2 TWh/a in 2050. Given the currently low amount of Renewable Energy Infrastructure (REI) in Switzerland amounting to ca. 3.5 TWh/a [1], this implies ca. 700 new wind turbines and PV panels on every 3rd building (excl. historic buildings). Due to environmental and societal concerns large-scale hydro power, a “traditional” REI in many alpine countries like Switzerland, Austria and Slovenia, has a limited expansion potential, which (for Switzerland) was downgraded even further in 2019 [2].

As a matter of fact, energy infrastructure like wind turbines and open-space photovoltaic panels are well-known for their impacts on the perceived landscape quality, which is also partially driven by

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Abbreviations

DCM	discrete choice model
HB	Hierarchical Bayes
LTF	landscape-technology fit
PTF	place-technology fit
Power lines	High voltage overhead power lines
PV	Photovoltaic
REI	Renewable energy infrastructure
RFC	Randomized first choice;
RQ	Research question
SoP	Share of Preferences

the fact that these REI are only efficient if placed on highly exposed sites like on mountain ridges, open plain fields etc. These sites often exhibit scenic views, are frequently considered cultural heritage sites or are preferred recreational landscapes. It has been shown that a careful integration of REI into these landscapes could lead to a successful transformation of "traditional" landscapes to "energy landscapes" [3,4]. For this transformation to be successful, it would be an advantage to be accompanied by social science studies that address the impact of REI on the perceived landscape quality, a major reason for resistance against REI [5]. Social acceptance of renewable energy infrastructure has often been the focus of studies in the past and it is clearly shown that the perceived impact of the energy transition on landscape quality is an important factor related to it [5–11].

Concerning visual impacts of individual energy infrastructure on the landscape, there is already broad well documented knowledge in the literature related to wind turbines [7,12–14], photovoltaic [15–17] and power lines [18–20]. However, results often have limited applicability to hilly and mountainous terrain like the wide Alpine arc including Switzerland. Additionally, most studies deal with one energy infrastructure type and lack of a combination of different sources in multiple landscape types. Consequently, we identify a lack of knowledge on how people assess a mix of REI in landscape types ranging from near-natural high-mountain sites to agricultural landscapes and peri-urban settlements.

Recently it was shown that besides highly relevant visual landscape impacts, also other aspects contribute to how people evaluate this landscape transformation driven by energy infrastructure. Salak et al. [21] presented evidence about the significant role of meanings both ascribed to landscapes and to REI when people evaluate landscape transformation processes. It turned out that meanings are at the core of individual evaluation processes and determine largely whether a technology fits the place [LTF, 21]. The "landscape technology fit" (LTF) which incorporates the individual evaluation of separate aspects (here landscape and REI) is similar to what has been suggested as "place-technology fit" (PTF) [22–24], but it is an up-scaled measure that incorporates the landscape context or in other words the meta level of landscape perception. It was also shown, that LTF is able to predict people's choices regarding landscape transformation processes significantly.

This article picks up the knowledge gaps listed above and addresses the following main question:

What preference patterns emerge when people evaluate REI in different host landscapes?

This main question was further subdivided to the following research questions:

RQ1: "The landscape component": What's the preference pattern of the various *landscape types* when hosting REI?

RQ2: "The energy component": What's the preference pattern of the various *REI mixes* when placed in various landscape types?

RQ3: "The energy mix component": What's the preference pattern of mixed versus single REI in changing host landscapes?

The focus of this study was deliberately placed on wind turbines, photovoltaic systems and high-voltage overhead power lines, which have a particular visual-aesthetic effect on the landscape. Under current legislation, ground-mounted PV systems are only marginally in use in Switzerland. However, this could change with a possible future renunciation of fossil fuels in the energy system in order to reduce CO_2 emissions.

2. Material and methods

2.1. Study design

To answer the above-mentioned research questions appropriately, a survey was conducted using an online panel of Swiss citizens. Within this online panel survey, we conducted a choice experiment. Based on the results of this choice experiment, Hierarchical Bayes analysis was used to estimate individual-specific profiles (individual weights according to each attribute level of the choice experiment). Those profiles where further used as input for Randomized First Choice simulation (RFC) which allowed to estimate the likelihood of choosing a certain scenario among all other possibilities.

2.2. Data collection

2.2.1. Study area

This study was conducted in Switzerland. Approximately 70% of the country are to be considered as mountainous where about 30% of the population live. This area comprises hilly pre-alpine landscapes predominantly characterized by agriculture and forests, touristic alpine areas with infrastructure, e.g. for skiing, alpine urban valleys, and near natural mountainous landscapes. 70% of the population however, lives on the central plateau with (peri-)urban and intense agriculture landscapes, which amounts to about 30% of the area. The north-western part of the country is dominated by the hilly terrain of the Jura mountains, a grazed woodland area with a relatively low population density. Hydropower and nuclear power currently play an important role in the Swiss energy production. But as mentioned before, hydropower has hardly any additional potential and nuclear power is not considered an option due to its potential risks (phase out until 2050). New REI actually play a minor role (5% of the electricity generation in 2020) [1]. However, the energy strategy for 2050 was backed up by a referendum and draws the path to replace the loss of nuclear energy by new REI. The current use of hydropower of ca. 36 TWh/a can only be marginally increased (ca. 1–3 TWh/a) [2] due to social and environmental costs. According to Kienast et al. [25] wind energy has a technical potential (not considering losses by competition or conflict with other ecosystem services) of 41 TWh/a, PV infrastructure on roofs 11 TWh/a, PV plants on open lands 30 TWh/a and biomass energy generated from forests 5 TWh/a.

2.2.2. Study sample

From November 2018 to March 2019, we conducted an online panel survey of Swiss inhabitants ($N = 1062$). Right before the main study and following Hensher et al. [26] a pretest ($N = 144$) was conducted to gain information about attribute priors for the choice design development. Due to cleaning procedures (total time of each respondent, time each respondent used in specific sections, consistency of responses etc.) about 18% ($N = 182$) of the respondents were dropped, resulting in a total of $N = 844$ respondents for further analysis. Details about study sample, online panel provider, quotas etc. can be found in Salak et al. [27] and the related data article [21].

2.3. Questionnaire

The questionnaire consisted of two major parts, where the first part contained the discrete choice experiment and the second part the questions addressing meanings and experiences of the respondents when watching the scenes. Within this study the focus of analysis was set on the DCE component.

2.3.1. Discrete choice approach

Discrete choice models have been developed across a wide range of disciplines and are often used in landscape research for many years. They include a utility function, which helps to better understand people's preferences for situations characterized and constrained by a set of alternatives (each determined by the attributes and the combination of their respective levels). The aim is to provide knowledge on the importance of those specific attributes and to estimate the "costs" of alternatives characterized by these attributes [26]. Random utility models can be seen as describing the relation of attributes to the outcome of a choice, without reference to exactly how the choice is made [28]. They estimate the probability of complex decisions for hypothetical alternatives ("scenarios") based on specific attributes. Thus, the preference of an alternative depends on (1) its attribute levels, (2) its competing alternatives, and (3) the characteristics of the individual [29]. Utility is made up by the sum of part worths of its separate attributes, while part-worths represent the utility generated by a particular level of an attribute [30]. The total utility (respondent preferences) of an alternative is represented by the weighted sum of the individual probabilities [28].

Usually, the respondents assess two or more alternatives by comparing them simultaneously in a choice task. To add more realism to the decision-making an additional option that does not force the subject to make a decision (opt-out) is suggested [31]. However, due to cognitive complexity choice models should be limited in the number of attributes and alternatives [32]. Each alternative underlies a utility function. So, the choice of one alternative depends on the level of each of the attributes presented in that alternative.

As discrete choice models are often estimated based on hypothetical scenarios, their choices reflect stated preferences rather than actual behavior.

2.3.2. Discrete choice experiment applied in this study

In the choice experiment, a total of 15 consecutive choice tasks were presented to each respondent. Respondents had to choose between two "energy system transformation" alternatives presented as landscape visualizations and an opt-out alternative (see Fig. 1). Respondents were asked to make each choice assuming the presented alternatives were the only available alternatives. Attributes were selected based on literature research first, and further developed during an expert workshop [33], where 25 experts from the fields of landscape planning, wind and photovoltaic project development, as well as employees of the national energy and spatial planning authorities discussed and evaluated pre-selected attributes and their levels.

The alternatives (options) were unlabeled, meaning that there was no additional (verbal-argumentative) description of what people could see on each visualization. Literature shows, that this, among other aspects like randomization, helps to reduce fatigue [34] and suits to present realistic scenarios of landscape transformation especially in complex contexts [35]. Attributes and levels applied in the DCE are presented in Table 1 and are referenced to Salak et al. [21]. For each attribute (landscape, wind energy infrastructure, PV infrastructure, power lines) certain attribute levels were developed. The combination of different levels defines an alternative. A total of 224 alternatives (7 landscapes attribute levels * 4 wind attribute levels * 4 PV attribute levels * 2 power line attribute levels) would have been needed to cover all possible combinations. The application of a D-optimal (efficient) fractional factorial minimal overlap design with NGENE v.1.2.0 helped to limit the number of alternatives needed. Finally, 30 alternatives were assigned to one fixed set of 15 randomly-ordered choice tasks (see Table 2). Each choice task included two alternatives and one neither option (opt-out). Cleaning procedures led to a total of 12660 choice observations (15 choice tasks * 844 respondents). Further detailed information about the experiment setup and data handling are provided in the references [21,27]. People's preferences derived from the choice experiment were used as input data for the further analysis procedures (see section 2.4.2).

2.4. Data analysis and modeling

2.4.1. Data preparation

The data were screened following Kline [39]. Non-responses on any model variable were removed from the dataset. Due to the fact that respondents were "professional" panel participants, and based on experiences from the pre-test, a lower time boundary of 150 s was set for the identification of speeders. An upper time boundary was waived as respondents had the possibility to stay logged in as long as they prefer. Homogeneity in responses of the choice experiment (consistency) was detected as decisions of respondents who share a high frequency of repeated selection (min. 14 of 15 times) of solely one or the other alternative (e.g.: continuously selecting only the first, the second or the opt-out alternative). Respondents identified as consistent in this meaning were removed from the dataset. McFadden's Rho-Squared reports the individual-specific "fit" of a respondent to the dataset between 0 (weak fit) to 1 (good fit). In our study respondents who showed a McFadden's Rho-Squared below 0.15 were also excluded.

2.4.2. Multinominal Logit Hierarchical Bayes analysis (MNL HB)

In the next step, we performed a Hierarchical Bayes (HB) analysis based on the information derived from the choice experiment. HB analysis, first applied by Allenby et al. [40], allows to find scenarios that appeal to diverse respondents with their heterogenous preferences [41]. This is done by considering each individual to be a sample from a population of similar individuals in the meaning that information from other respondents is "borrowed" (upper level) to estimate individual preferences (lower level). Hierarchy refers to exactly those two levels. While in the upper level the importance weights are assumed to have a multivariate normal distribution described by a vector of means and a matrix of variances and covariances [42], in the lower level it is assumed that the probability of choosing particular alternatives is governed by a multinominal logit regression model (MNL). MNL is a regression analysis for categorial dependent variables to produce a maximum likelihood fit to respondents' choices in a questionnaire. HB analysis improves accuracy of predictions, reduces Independence of Irrelevant Alternative (IIA) [43], and allows post hoc segmentation of respondent data. For estimating a hierarchical random coefficients model a Monte Carlo Markov Chain algorithm was applied. We used 20000 estimations (10000 preliminary, 10000 draws after convergence) with optimized prior settings which were set according to Orme and Williams [44] and define a maximum expected hit rate of 54.2% with a prior variance of 1.5 and 675 degrees of freedom (see Appendix I). Prior variance describes a prior belief about how diffuse or peaked the distribution of tastes is across respondents. Degrees

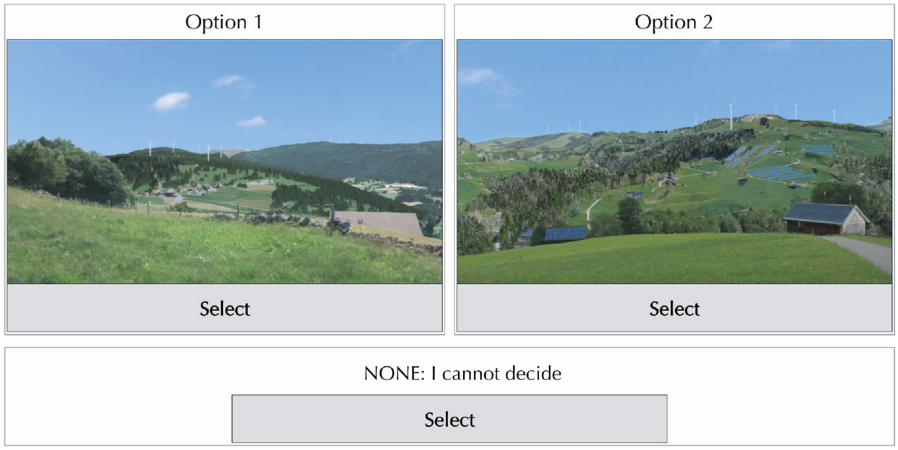


Fig. 1. Example of a choice task [21].

Table 1
Choice attributes and their levels [21].

Nr.	Levels	Description
	Attribute Landscape	
1	Alp	Near-natural, mostly high-elevation mountainous areas in the Alps
2	Pre_alps	Mid- to higher elevation areas with a patchy mix of agriculture and forests
3	Alp_tour	Touristic mountain areas in the Alps >1000 m elevation
4	Plat_agri	Plateau areas dominated by intense agricultural use
5	Plat_urb	Plateau areas dominated by settlements (excluding inner-city urban areas)[a]
6	Jura	Hilly mountain ridges of the Jura region
7	Alp_urb	Intra-mountain valleys dominated by settlements
	Attribute Wind energy infrastructure	
1	Wind no	No wind energy infrastructure
2	Wind min	Low level of wind energy infrastructure (3)[b]
3	Wind med	Medium level of wind energy infrastructure (6)[b]
4	Wind max	High level of wind energy infrastructure (10/15 in Jura ridges)[b]
	Attribute Photovoltaic infrastructure	
1	PV no	No PV infrastructure
2	PV min	Low level of PV infrastructure[c]
3	PV med	Medium level of PV infrastructure[c]
4	PV max	High level of PV infrastructure[c]
	Attribute High voltage overhead power line	
1	PL no	Absence of power line
2	PL yes	Presence of power line

[a] Landscapes of inner-city urban areas were not included in this study.
[b] Attribute levels of wind differ in number of wind turbines and VIWT [36,37]. While the maximum number wind turbines per landscape equals 10, in Jura 15 wind turbines were placed. The impact of wind infrastructure per pixel differentiates on average by 38% between attribute levels (min-med, med-max).
[c] Attribute levels of PV differ in OAISPP [15,36,38]. Area covered by PV infrastructure differentiates between attribute levels and landscapes. The impact of PV infrastructure per pixel differentiates on average by 40% between attribute levels (min-med, med-max).

of freedom influence how strongly the prior variance assumption is enforced within the model. Settings influence the degree of Bayesian smoothing (shrinkage) of individuals to the population means [44].

2.4.3. Randomized first choice approach (RFC)

The data derived from HB analysis were used as input data for the Randomized First Choice (RFC) simulation, as individual-level utilities. This approach, originally developed by Orme 1998 and further developed by Huber et al. [45], considers that people's choices are made with respect to two kinds of errors: attribute type errors (ε_a) and product-type errors (ε_p). Orme and Chrzan [42] describe it roughly like this: With every meal a respondent has to choose a type of beverage. For each decision the vector of utilities is perturbed by a vector of normally distributed attribute error (ε_a). This perturbation happens once per meal and per day and is used to compute the total utility of all alternatives in the simulation scenario. However, a second error (ε_p), distributed Gumbel, applies independently to each alternative (each type of beverage) and is added to the utilities and the attribute type error (ε_a). In each meal the respondent's choice is predicted using the first-choice rule (most favorite) but if the variance of errors is large enough, the respondent will often change her/his (generally) favorite selection across several beverages. The results of all meal type of beverage selections are averaged for each respondent, leading to decision splitting and probabilistic shares of preferences for the alternatives

Table 2
Description of choice tasks, choice attributes and attribute levels [27].

	Attributes and Attribute levels								
Choice	**1**				**2**				**3**
Choice Task	**Landscape**	**Wind**	**PV**	**PL**	**Landscape**	**Wind**	**PV**	**PL**	**Opt out possibility**
1	Alp	no	no	yes	Alp	med	min	no	Yes
2	Alp_urb	no	no	yes	Plat_urb	min	med	no	Yes
3	Alp	med	min	yes	Jura	max	no	yes	Yes
4	Alp_urb	max	med	no	Jura	med	min	no	Yes
5	Plat_urb	max	max	no	Alp	min	med	no	Yes
6	Plat_agri	min	min	no	Alp	no	max	yes	Yes
7	Jura	med	med	no	Alp_tour	max	min	yes	Yes
8	Pre_alp	max	max	no	Plat_urb	min	max	yes	Yes
9	Alp_tour	min	max	no	Plat_agri	no	med	yes	Yes
10	Pre_alp	min	no	yes	Alp_tour	med	med	yes	Yes
11	Jura	min	med	yes	Alp	no	max	no	Yes
12	Alp_urb	med	no	yes	Alp_urb	min	max	yes	Yes
13	Plat_urb	max	min	yes	Plat_agri	max	no	no	Yes
14	Plat_agri	med	max	no	Alp_urb	max	no	no	Yes
15	Alp_tour	no	med	yes	Alp_urb	med	min	yes	Yes

that sum up to 100% [see: 42]. We applied RFC simulation with standard settings for all respondents (n = 844) which resulted in estimations for each of the 224 potential development scenarios defined by DCE attribute levels (7 landscape levels * 4 wind energy infrastructure levels * 4 PV infrastructure levels * 2 power line levels = 224 scenarios).

3. Results

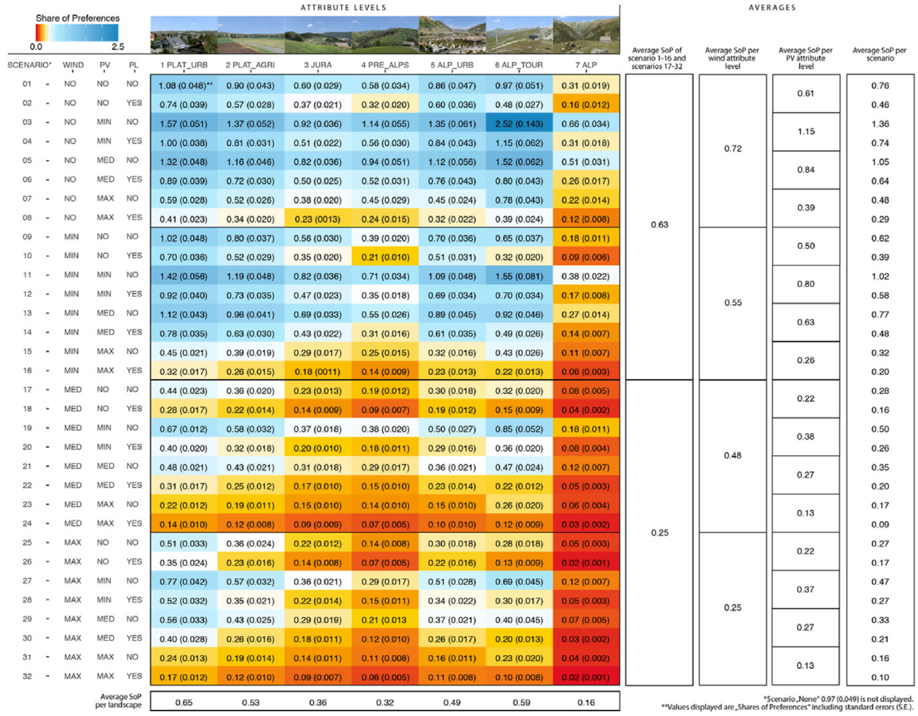
3.1. Discrete choice experiment

Based on the results of our discrete choice experiment (DCE) we first developed a Multinominal Logit Hierarchical Bayes (MNL HB) model and used this information to further perform a choice simulation based on a Randomized First Choice (RFC) approach. As a result, we gained relative indications of people's preferences related to renewable energy landscape scenarios. Quality model indicators of our study show average McFadden Rho-Squared (0.482) and average root likelihood (0.578), where the first represents the overall model fit and the latter the geometric mean across the respondent's tasks. The model reported Likelihood (−7119.27) shows significant improvement in the explained information of +51% in reference to a totally random model with the same number of attributes and attribute levels (−13908.43).

Results are presented in Fig. 2 containing information on the simulated likelihood of selection on each potential alternative (scenario) represented as “Share of Preference” (SoP). They are first presented with focus on landscape, and afterwards on renewable energy infrastructure.

3.2. Landscape related results

People's assessment of REI alternatives (scenarios) in different landscape types (Fig. 2) shows that REI receives high preference on the infrastructure-rich Plateau and mountain sites (PLAT_URB, ALP_TOUR) but gets low preference in close-to-nature landscapes and landscapes with a traditional land-use (ALP, but also JURA and PRE_ALP). There is a moderate fit in high-intensity agricultural areas of the plateau (PLAT_AGRI) and the settlement-dominated inner alpine valleys. Overall, landscapes without any REI (scenario 01) receive higher preference compared to scenarios including REI. However, there are a few exceptions: scenarios 03, 05, 11 (in all landscapes) and scenario 13 (in most landscapes) receive considerably higher preference despite the fact that they have a minimum amount of REI.



SCENARIO*		WIND	PV	PL	1 PLAT_URB	2 PLAT_AGRI	3 JURA	4 PRE_ALPS	5 ALP_URB	6 ALP_TOUR	7 ALP	Average SoP of scenario 1-16 and scenarios 17-32	Average SoP per wind attribute level	Average SoP per PV attribute level	Average SoP per scenario
01	-	NO	NO	NO	1.08 (0.048)**	0.90 (0.043)	0.60 (0.029)	0.58 (0.034)	0.86 (0.047)	0.97 (0.051)	0.31 (0.019)	0.63	0.72	0.61	0.76
02	-	NO	NO	YES	0.74 (0.039)	0.57 (0.028)	0.37 (0.021)	0.32 (0.020)	0.60 (0.036)	0.48 (0.027)	0.16 (0.012)				0.46
03	-	NO	MIN	NO	1.57 (0.051)	1.37 (0.052)	0.92 (0.036)	1.14 (0.055)	1.35 (0.061)	2.52 (0.143)	0.66 (0.034)			1.15	1.36
04	-	NO	MIN	YES	1.00 (0.038)	0.81 (0.031)	0.51 (0.022)	0.56 (0.030)	0.84 (0.043)	1.15 (0.062)	0.31 (0.018)				0.74
05	-	NO	MED	NO	1.32 (0.048)	1.16 (0.046)	0.82 (0.036)	0.94 (0.051)	1.12 (0.056)	1.52 (0.062)	0.51 (0.031)			0.84	1.05
06	-	NO	MED	YES	0.89 (0.039)	0.72 (0.030)	0.50 (0.025)	0.52 (0.031)	0.76 (0.043)	0.80 (0.043)	0.26 (0.017)				0.64
07	-	NO	MAX	NO	0.59 (0.028)	0.52 (0.026)	0.38 (0.020)	0.45 (0.029)	0.45 (0.024)	0.78 (0.043)	0.22 (0.014)			0.39	0.48
08	-	NO	MAX	YES	0.41 (0.023)	0.34 (0.020)	0.23 (0013)	0.24 (0.015)	0.32 (0.022)	0.39 (0.024)	0.12 (0.008)				0.29
09	-	MIN	NO	NO	1.02 (0.048)	0.80 (0.037)	0.56 (0.030)	0.39 (0.020)	0.70 (0.036)	0.65 (0.037)	0.18 (0.011)		0.55	0.50	0.62
10	-	MIN	NO	YES	0.70 (0.036)	0.52 (0.029)	0.35 (0.020)	0.21 (0.010)	0.51 (0.031)	0.32 (0.020)	0.09 (0.006)				0.39
11	-	MIN	MIN	NO	1.42 (0.056)	1.19 (0.048)	0.82 (0.036)	0.71 (0.034)	1.09 (0.048)	1.55 (0.081)	0.38 (0.022)			0.80	1.02
12	-	MIN	MIN	YES	0.92 (0.040)	0.73 (0.035)	0.47 (0.023)	0.35 (0.018)	0.69 (0.034)	0.70 (0.034)	0.17 (0.008)				0.58
13	-	MIN	MED	NO	1.12 (0.043)	0.96 (0.041)	0.69 (0.033)	0.55 (0.026)	0.89 (0.045)	0.92 (0.046)	0.27 (0.014)			0.63	0.77
14	-	MIN	MED	YES	0.78 (0.035)	0.63 (0.030)	0.43 (0.022)	0.31 (0.016)	0.61 (0.035)	0.49 (0.026)	0.14 (0.007)				0.48
15	-	MIN	MAX	NO	0.45 (0.021)	0.39 (0.019)	0.29 (0.017)	0.25 (0.015)	0.32 (0.016)	0.43 (0.026)	0.11 (0.007)			0.26	0.32
16	-	MIN	MAX	YES	0.32 (0.017)	0.26 (0.015)	0.18 (0011)	0.14 (0.009)	0.23 (0.013)	0.22 (0.013)	0.06 (0.003)				0.20
17	-	MED	NO	NO	0.44 (0.023)	0.36 (0.020)	0.23 (0.013)	0.19 (0.012)	0.30 (0.018)	0.32 (0.020)	0.08 (0.005)	0.25	0.48	0.22	0.28
18	-	MED	NO	YES	0.28 (0.017)	0.22 (0.014)	0.14 (0.009)	0.09 (0.007)	0.19 (0.012)	0.15 (0.009)	0.04 (0.002)				0.16
19	-	MED	MIN	NO	0.67 (0.012)	0.58 (0.032)	0.37 (0.018)	0.38 (0.020)	0.50 (0.027)	0.85 (0.052)	0.18 (0.011)			0.38	0.50
20	-	MED	MIN	YES	0.40 (0.020)	0.32 (0.018)	0.20 (0.010)	0.18 (0.011)	0.29 (0.016)	0.36 (0.020)	0.08 (0.004)				0.26
21	-	MED	MED	NO	0.48 (0.021)	0.43 (0.021)	0.31 (0.018)	0.29 (0.017)	0.36 (0.021)	0.47 (0.024)	0.12 (0.007)			0.27	0.35
22	-	MED	MED	YES	0.31 (0.017)	0.25 (0.012)	0.17 (0.010)	0.15 (0.010)	0.23 (0.014)	0.22 (0.012)	0.05 (0.003)				0.20
23	-	MED	MAX	NO	0.22 (0.012)	0.19 (0.011)	0.15 (0.010)	0.14 (0.010)	0.15 (0.010)	0.26 (0.020)	0.06 (0.004)			0.13	0.17
24	-	MED	MAX	YES	0.14 (0.010)	0.12 (0.008)	0.09 (0.009)	0.07 (0.005)	0.10 (0.010)	0.12 (0.009)	0.03 (0.002)				0.09
25	-	MAX	NO	NO	0.51 (0.033)	0.36 (0.024)	0.22 (0.012)	0.14 (0.008)	0.30 (0.018)	0.28 (0.018)	0.05 (0.003)		0.25	0.22	0.27
26	-	MAX	NO	YES	0.35 (0.024)	0.23 (0.016)	0.14 (0.008)	0.07 (0.005)	0.22 (0.016)	0.13 (0.009)	0.02 (0.001)				0.17
27	-	MAX	MIN	NO	0.77 (0.042)	0.57 (0.032)	0.36 (0.021)	0.29 (0.017)	0.51 (0.028)	0.69 (0.045)	0.12 (0.007)			0.37	0.47
28	-	MAX	MIN	YES	0.52 (0.032)	0.35 (0.021)	0.22 (0.014)	0.15 (0.011)	0.34 (0.022)	0.30 (0.017)	0.05 (0.003)				0.27
29	-	MAX	MED	NO	0.56 (0.033)	0.43 (0.025)	0.29 (0.019)	0.21 (0.013	0.37 (0.021)	0.40 (0.045)	0.07 (0.005)			0.27	0.33
30	-	MAX	MED	YES	0.40 (0.028)	0.26 (0.016)	0.18 (0.011)	0.12 (0.010)	0.26 (0.017)	0.20 (0.013)	0.03 (0.002)				0.21
31	-	MAX	MAX	NO	0.24 (0.013)	0.19 (0.014)	0.14 (0.011)	0.11 (0.008)	0.16 (0.011)	0.23 (0.020)	0.04 (0.002)			0.13	0.16
32	-	MAX	MAX	YES	0.17 (0.012)	0.12 (0.010)	0.09 (0.007)	0.06 (0.005)	0.11 (0.008)	0.10 (0.008)	0.02 (0.001)				0.10
				Average SoP per landscape	0.65	0.53	0.36	0.32	0.49	0.59	0.16				

*Scenario „None" 0.97 (0.049) is not displayed.
**Values displayed are „Shares of Preferences" including standard errors (S.E.).

Fig. 2. Share of Preferences (SoP) for all potential energy scenarios resulting from the DCE attributes. The number in brackets refer to the standard errors (S.E.). Color coding: white color represents the median of all values (SoP 0.34). Blue gradient colors represent values above the median (maximum SoP value at 2.52) while red gradient colors represent values lower than the median (minimum SoP value at 0.02).

3.2.1. *Settlement and agriculture-dominated landscapes of the Plateau (PLAT_URB, PLAT_AGRI)*

Fig. 2 also shows that the settlement-dominated areas of the Plateau (PLAT_URB) could potentially become the backbone of a sustainable energy transition according to people's preference. With some exceptions (scenarios 03, 04, 05, 07, 11, 19, 23; see above) all REI scenarios show their highest values on the urbanized Plateau, even if some scenarios with high REI get low preference. Further, we point out the scenarios for settlement-dominated intra-mountain valleys (ALP_URB), where high wind REI (scenarios 25–32) shares higher preference compared to scenarios having medium wind REI (scenarios 17–24). No other landscape type shows this pattern. This highlights and confirms the suitability of this landscape type for energy transition based on public preferences. Preferences of scenarios in settlement-dominated areas of the Plateau (PLAT_URB) are on average 20% higher than on agricultural-dominated areas of the Plateau (PLAT_AGRI), 45% higher than in touristic mountain areas exceeding 1000 m (ALP_TOUR) and 86% higher than in near natural mostly high-elevation mountainous landscapes in the Alps (ALP). The latter was the least preferred landscape for all energy scenarios. Besides the overall strong preferences in settlement-dominated areas of the plateau, also scenarios in agriculture-dominated areas of the plateau (PLAT_AGRI) show mid to strong preferences. Share of preferences across scenarios in the agricultural dominated areas of the plateau are quite similar to results in the settlement dominated intra-mountain valleys (ALP_URB).

3.2.2. *High-elevation mountains, touristic mountain areas exceeding 1000 m and urbanized intra-mountain valleys of the Alps (ALP, ALP_TOUR, ALP_URB)*

In particular near natural high-elevation mountainous landscapes (ALP) show a strong rejection of REI developments throughout all scenarios. This indicates a place-protective behavior of respondents. Yet, this does not mean that people generally dislike REI developments in high-mountain landscapes, as shown by the positive evaluation patterns in touristic mountain areas (ALP_TOUR). But people would like to restrict REI to areas where touristic infrastructure (like cable cars) is already a considerable part of the landscape character. Touristic mountainous areas in the Alps are highly favored for specific REI scenarios, i.e., they show the highest values in scenarios that are characterized by either solely PV infrastructure (scenarios 03, 04, 05, 07) or PV infrastructure in combination with a minimum or medium presence of wind energy infrastructure (scenarios 11, 19, 23), the latter on a general very low preference level.

For example: Scenario 19 (medium wind, minimum PV, no power lines) shows the overall highest values of all scenarios with a medium to maximum number of wind energy infrastructure in touristic mountainous areas (ALP_TOUR). However, there are many alternative energy scenarios with higher preference ratings even in this landscape. Many of them share a low energy production perspective, e.g. shown in scenario 03 (no wind, min PV, no power lines) which turned out to be the overall highest rated scenario of all landscapes. Landscapes in the settlement dominated intra-mountain valleys of the Alps (ALP_URB) show specific preferences for energy mix scenarios, too. Nonetheless, compared to preferences driving landscapes (like PLAT_URB), SoP values of scenarios in ALP_URB show both less significance and lower values across scenarios. Moreover, settlement dominated intra-mountain valleys (ALP_URB) show similarities rather with respect to scenarios in touristic mountain landscapes (ALP_TOUR) than to near natural mostly high-elevation mountainous areas of the Alps (ALP), but on a (much) lower level.

3.2.3. *Mid-elevation mountains (JURA, PRE_ALPS)*

Preferences for scenarios in mid-to-high-elevation areas having a patchy mix of agriculture and forests (PRE_ALP, JURA) show a bipolar preference pattern driven by the number of wind REI: scenarios 17 to 32 (lower half of the table) are consistently rejected in these landscapes comparable to the rejections observed in the near-natural, mostly high-elevation mountainous areas in the Alps (ALP). However, scenarios 01 to 16 (upper part of the table) show a moderate preference. None of the scenarios stands out to get high or low preference in these mid-elevation mountainous landscapes. They all seem acceptable, but do not elicit much acceptance or reactance from respondents.

3.3. Renewable energy infrastructure related results

Our results show a huge diversity in the preferences not only across renewable energy infrastructure types and landscapes but also with respect to which and how many REI are present in the scenarios. Overall, higher preferences are assigned to scenarios with low numbers of REI and lower preferences to those with higher numbers of REI (see column “Average SoP of scenario 1–16 and scenarios 17–32” in Fig. 21).

3.3.1. Wind energy infrastructure

Regarding wind energy infrastructure, preferences show an overall decrease with increasing REI. Specifically, scenarios in the settlement dominated areas of the plateau (ALP_URB) are exemption, as an increasing number of wind energy infrastructure leads to increasing preferences (still on a low level). Besides, the main finding of decreasing preference with increase of wind energy infrastructure is congruent through all landscapes. This shows that a specific preference pattern, i.e. rejection regarding wind energy infrastructure, is manifested in people's perception.

3.3.2. PV energy infrastructure

PV energy infrastructure presents a quite complex pattern. First, scenarios lacking PV infrastructure show lower preference compared to the same scenarios including a minimum number of PV infrastructure (see “Average SoP per PV attribute level”). This can exemplarily be demonstrated by comparison of scenarios 09 and 11, where beside PV all other attributes were constant. It shows, that the absence of PV infrastructure triggered a negative effect on people's scenario assessment. Second, if the number of PV infrastructure keeps rising to a medium or even maximum level, preferences decrease steadily (compare scenarios 11 to 13 and 15).

3.3.3. Power line infrastructure

Power lines show a general rejection pattern in all scenarios and landscapes. No energy scenario in particular is more preferred when including a power line than without.

3.3.4. General findings

In general, scenarios containing solely PV (in small numbers) represent the most favorized landscape transformation (scenario 03). Scenarios consisting of a medium or high number of a single energy infrastructure type (only wind, only PV) have lower preference than scenarios including a specific mix of infrastructure. This can be shown by comparing e.g. scenario 09 (only wind) with scenarios 11 and 13, respectively (wind combined with PV). This result also holds for scenarios with higher amounts of REI, e.g. scenario 17 (medium wind) vs. scenarios 19 and 20 or scenario 25 (maximum wind) vs. scenarios 27 and 29.

4. Discussion

The present study is a representative study on the Swiss population's assessment of renewable energy infrastructures (*wind-, PV-, power line infrastructure*) in characteristic Swiss landscapes. The online panel survey (n = 1063) with a discrete choice experiment was a suitable method to gather a representative sample. Hierarchical Bayes analyses proved to be appropriate to extract individual preference levels (profiles) which were used as input for Randomized First Choice (RFC) simulation. The results represent robust estimations of the current preferences of the population towards/against REI developments in different landscapes. Hence, we could find reliable answers to the three research sub-questions: First, the landscape type where REI is placed plays a decisive role whether REI is preferred or not. REI in near-natural landscapes is rejected and respondents seek for solutions where REI is placed in existing infrastructure (RQ1). Second, the higher the amount of wind REI and power lines the higher the rejection rate. Worth mentioning, absence of PV infrastructure results in less positive evaluations of the scenarios (RQ2). Finally, a mix of different energy infrastructure types (wind and PV) in low to medium numbers is positively assessed. High amounts of one single REI type get high rejection rates (RQ3).

In the following, these results are further discussed under four thematical foci:

4.1. The importance of both landscape types and REI mix in rejecting scenarios

The general preference patterns indicate that both, the landscape and the REI mix are important. This confirms recent findings [21], which showed that both landscape and REI attributes significantly predict people's choices. Nevertheless, some studies [46] suggest REI developments in high-elevation mountainous regions, far away from settlements to avoid conflicts. Apart from ecological aspects that were not part of this study, we could show that REI development in such pristine landscapes trigger *place protective behavior* as clearly illustrated by the reactions of the study participants: all scenarios in the landscape type ALP were clearly rejected (compared to other landscapes). On the other side, people do respect and seem to partially understand the need for REI developments in landscapes and are willing to accept them in mid to high-elevation mountainous areas but at places where settlements, touristic infrastructure etc. already exist (ALP_TOUR).

We further show that a fine-tuned mix of energy infrastructure types could make a difference whether REI is accepted or not in a specific landscape. We found evidence that people expect a certain amount of PV in any scenario and landscape, except in the pristine mountain landscape, when they think about REI related landscape transformation processes. Further, our analysis shows that the mix of energy infrastructure types in combination with the number of REI and the landscape all together are highly relevant for rejection or acceptance. The fact that a specific mix of REI adapted to a landscape type can be critical to acceptance or reactance is a new, previously unknown finding. Up to present [47], energy mix scenarios had hardly received any attention in quantitative social research and if so, without the landscape context. Nonetheless, to improve scenario alternatives and to offer “more realistic” unembellished alternatives, future studies may assess scenario development with the additional integration of infrastructure of traditional energy sources like fossil, hydro or nuclear power sources (“real alternatives”). Further, photovoltaic infrastructures should be split up in building-mounted photovoltaic and open space photovoltaic. The downside of this could be that some REI would not make sense in certain environments, such as building-mounted PV in landscapes with only a few buildings or, conversely, ground-mounted photovoltaics in dense urban areas with space constraints. Finding a way to meet these scenario development (and presentation) requirements while still presenting realistic alternatives will be critical.

Another aspect that this study does not explore is to find the most environmentally and socially acceptable locations for given amounts of energy production. Such a spatially explicit trade-off process would be necessary to avoid an increase in social costs (e.g., resistance) [48]. Distinct research projects address these issues, e.g. Eichhorn et al. [49].

4.2. Individual landscape meanings and their societal impact

Several studies show that landscape perception is driven by universal, cultural and individual factors [50–55]. The present study confirms these findings in the thematic context of energy landscapes. Concerning individual factors, we found that individual meanings associated to landscapes can be a decisive factor for rejection or acceptance. This can be illustrated with e.g. the place-protective behavior against REI in near-natural landscapes (ALP). Although same amounts of REI were involved, other landscapes were evaluated less critical (PLAT_URB, ALP_TOUR, ALP_URB). Several studies suggest [24,56–58] that this behavior is linked to personal values and attitudes. In particular, when the meanings ascribed to these places also allow for a positive connotation of REI, place (landscape) and technology seem to “fit”. A recent related study [21] revealed that individual decisions about what people evaluate as “fitting” or “not fitting” drives people's final decisions about REI. This implies that something is perceived as “fitting” if there is an overlap in personal values and the assignment of meaning and significance.

Our study shows, that “no REI” scenarios (01) get lower preference than “a little”, and “high REI”. This demonstrates that respondents do not yet realize how much REI are needed to be implemented in our landscapes for a successful energy transition. This may be rooted in a lack of awareness about the energy production capability of REI in general as respondents imagine that “a little” REI presence in our landscapes would be sufficient for the turnaround. Raising awareness either of the needed landscape character change or of applying energy saving measures is therefore decisive.

4.3. Societal move towards accepting a sustainable energy transformation

Our results show, that society acknowledges the energy system change by accepting a certain degree of REI in almost all landscapes presented. However, the amounts of REI that are accepted in the survey show that society is not yet aware of the giant dimension of transformation needed (number of infrastructures). In order to obtain the 25 TWh/a to replace the current nuclear power plants and to further fully decarbonize the energy demand, people would (and will) need to accept much higher REI amounts. At the moment of this study, it is shown that this is not the case yet, as e.g., our “power horse” scenarios with a significant number of infrastructure and a potentially high energy production are rated (rather) low. We confirm findings of Pasqualetti [59], Apostol et al. [60] and others that the energy system change per se is not questioned but not for the sake of altering pristine landscapes. For planning we recommend to concentrate REI in areas that have already been altered by infrastructure and to build on landscapes where a decent landscape-technology fit can be obtained (see paragraph above).

The matter of high-voltage overhead power lines

As demonstrated in a number of studies [19,20] overhead power lines have a negative impact on people's ratings, as no scenario was rated better with power lines than without. This leaves no further room for discussion and power grid operators must find ways to better communicate the benefits and the risks of the highly needed high-voltage overhead lines for a successful decentral energy transformation. Otherwise, to not endanger an emerging energy transition, society and politics need to transparently discuss about alternatives to overhead lines (like underground power lines) and their limitations.

Revival of nuclear power as “green energy”?

In countries with a post-Fukushima nuclear phase-out regime, nuclear energy has so far not been considered as a serious alternative to reduce CO_2 emissions. However, recently this discussion has been politically reopened in various EU member states and affiliated countries including Switzerland. The primary reason is the on-going discussion in the EU, which has classified nuclear power as “green” in the so-called “taxonomy for environmentally sustainable economic activities”. The current paper does not deepen this merely political aspect. However, given recurrent geopolitical tensions on crude materials and fuel, including uranium, shows that development of REI does not only contribute to sustainability but also to resilience in times of potential conflicts due to decentralization and political independence.

5. Conclusions

Overall, our results are not meant to provide priority areas for REI. They rather highlight landscape types that have the potential for social conflicts when it comes to placing REI. Such knowledge could be used for a spatially explicit site selection or optimization modeling procedure. For example, a recent wind modeling study for Switzerland [61] picks the smooth hills of the Jura mountains as the most favorable area for wind turbines from an energetical and technical perspective. This, however, is in contrast to the findings from the present study as scenarios including wind energy infrastructure especially in the Jura do not find decent social approval (in the overall population). Similar observations are made related to photovoltaic modeling studies in Switzerland [46]. Taking into account the differentiated assessments of REI in Swiss landscape types could help to better integrate people's preferences from a landscape perspective into spatial concepts of renewable energy infrastructure development.

6. Declaring 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.

7. Data accessibility

Base data (individual raw utility scores) for choice simulation procedure is provided in the Appendix section of this manuscript. Further data related to the choice experiment is accessible via online repository “EnviDat”: https://www.envidat.ch. Data identification number: https://doi.org/10.16904/envidat.206.

CRediT authorship contribution statement

B. Salak: Resources, Methodology, Conceptualization, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review & editing. **F. Kienast:** Funding acquisition, Conceptualization, Writing – review & editing, Validation, Supervision. **R. Olschewski:** Methodology, Formal analysis, Software, Validation, Writing – review & editing. **R. Spielhofer:** Visualization. **U. Wissen Hayek:** Funding acquisition, Project administration, Visualization, Writing – review & editing. **A. Grêt-Regamey:** Funding acquisition, Visualization, Writing – review & editing, Supervision. **M. Hunziker:** Funding acquisition, Project administration, Conceptualization, Writing – review & editing, Validation, Supervision.

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.

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