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Are Interactive Web-Tools for Environmental Scenario Visualization Worth the Effort? An Experimental Study on the Swiss Electricity Supply Scenarios 2035

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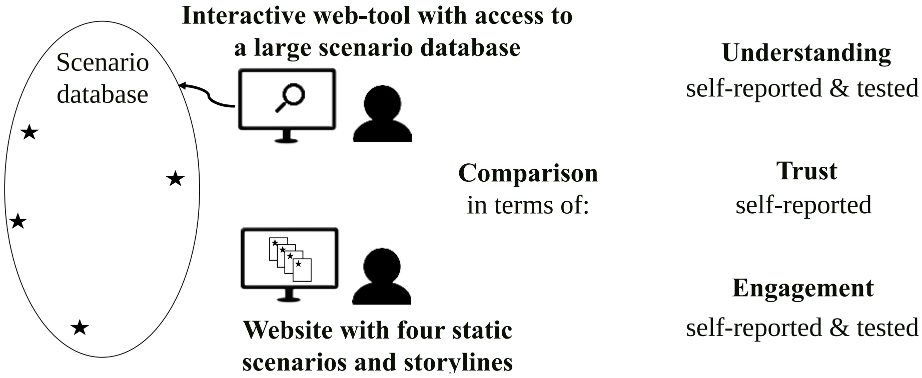
Abstract

Interactive web-tools are regarded as powerful methods to present large scenario ensembles from environmental modelling in an understandable and engaging way. Yet, there is little empirical evidence whether they are more effective than traditional approaches such as story-and-simulation. We conducted a between-groups experiment, where two groups of participants (total N=313) differed in the scenario information received: (1) an interactive web-tool for exploring a large database of Swiss electricity scenarios 2035 and their environmental, health, and economic impacts; (2) a website presenting four of these scenarios with storylines. Results indicate that our interactive web-tool did not lead to benefits in self-reported understanding and engagement because there was no difference between the conditions. In fact, participants using the interactive web-tool performed worse in an understanding quiz than those using the four scenarios. These unexpected findings call for more empirical research whether interactive tools for scenario visualization meet the needs of intended users.

Keywords

interactive tools; scenarios; usability evaluation; public engagement; decision support; electricity supply

Graphical abstract



Highlights

- Interactive scenario visualization was not superior to story-and-simulation approach
- Tested understanding was lower with an interactive tool than with four scenarios
- Self-reported understanding, engagement and trust were similar in both conditions
- High website navigation skills and numeracy correlated with high understanding
- High prior experience with the tool's topic correlated with high engagement

1. Introduction

Interaction between scientists and the public, stakeholders and decision makers is often seen as a powerful way to increase the accessibility and impact of scientific results (Lemos et al., 2012; Mach et al., 2017; Voinov et al., 2016). Due to the growing capabilities of web services and the far-reaching connectivity of the Internet, web applications are increasingly appearing in order to allow us to interact with environmental science products, such as databases, models, scenarios and maps (Moss, 2016). Based on the intended interaction between the developers of such interactive web-tools and their users, we observe four types of usage: (1) outreach and education, (2) two-way engagement, (3) scientific research and (4) decision support. First, interactive web-tools have been used to explain complex environmental issues, for instance climate change or energy transition, by providing interfaces for the public to actively explore underlying systems and future scenarios (DECC, 2013; U.S. Federal Government, 2014). Second, some tools have been asking users to submit their views and comments on a subject (Babbar-Sebens et al., 2015; Lai et al., 2011) with the aim to create a two-way dialogue and “reflect useful social intelligence back” (Pidgeon et al., 2014, p. 13606). Third, the results of the interaction with such tools have also been used to inform scientific research, allowing, for example, scientists to analyze submitted answers in order to understand how users formulated them (Bessette et al., 2016; Demski et al., 2017; Volken et al., 2018). Fourth, tools have been developed to support actual decisions by providing interactive interfaces with scientific products in order to assist users, such as policy-makers and stakeholders, in finding a scientific basis for decision-making (Sandink et al., 2016). Apart from the use of these interactive web-tools in the environmental fields, diverse domains have followed the same trend, including medicine (Ancker et al., 2011), life quality (OECD, 2011) and social sciences (Jones et al., 2016).

There have been claims of multiple benefits of interactive web-tools as compared to more traditional scientific outputs, such as technical reports, policy briefs, academic publications, and other written documents. First of all, it has long been assumed that they can promote understanding by allowing the user to actively explore information (McInerny et al., 2014; Spiegelhalter et al., 2011; Strecher et al., 1999). Whereas traditional scientific outputs show “static” visualizations and explanations of data or model outputs, interactive web-tools offer control over this information. By clicking on interactive elements, like buttons and sliders, the user can change parameters and see the effects, uncovering the data at a custom pace. This is claimed to be particularly helpful in explaining multidimensional problems and can possibly help users in developing robust mental models on a subject (Grainger et al., 2016; McInerny et al., 2014). Other control elements allow the user to change the form of information by zooming, sorting and highlighting (Heer et al., 2012) or even by switching representation format (e.g. from qualitative to quantitative) in order to adapt to the preferences and competences of the users (Spiegelhalter et al., 2011). These adaptation opportunities are also assumed to improve the visibility and accessibility of related uncertainties by directing attention, for example, to low-probability events (Ancker et al., 2011; Spiegelhalter et al., 2011). Furthermore, interactive web-tools are believed to support user engagement even with complex subjects that users have little initial familiarity (Pidgeon et al., 2014). The “learning-by-doing” experience provided by such tools is believed to increase the time and effort spent by users, making them more involved in learning (Strecher et al., 1999, p. 134). Adding gaming mechanisms and appealing graphics to interactive web-tools is also considered to provide further opportunities to engage users through an entertaining and playful environment (I. Mayer et al., 2014; Voinov et al., 2016).

Using interactive web-tools has been also suggested as a solution for effectively customizing information to different audiences, e.g. in the case of communicating scenarios based on long-term climate and energy analysis (DeCarolis et al., 2017; Guivarch et al., 2017; IPCC, 2016; Moss, 2016; Trutnevyte et al., 2016). As models can generate an infinite number of plausible scenarios to capture future uncertainty, scenario developers reduce them to a small number in order to present them (Berntsen and Trutnevyte, 2017), usually in easily understandable forms such as narratives (Alcamo, 2008; McInerny et al., 2014). This strategy might not match the needs of scenario users who need more customized scenarios or it may lead to a disregard of potentially important uncertainties that exist in other scenarios (Braunreiter and Blumer, 2018; Trutnevyte et al., 2016). While there are techniques to diversify a set of scenarios and increase the uncertainty considered (Berntsen and Trutnevyte, 2017; Carlsen et al., 2016; Tietje, 2005), other solutions suggest a more interactive way of iteratively "interrogating" models to explore a larger number of scenarios (DeCarolis et al., 2016; Lempert, 2002). In this case, interactive web-tools could provide access to large databases of scenarios along with transparent methods to extract useful sub-sets tailored to the needs of users, e.g. the most internally consistent or the most policy-relevant scenarios (Trutnevyte et al., 2016). Such methods are rarely found in existing tools, such as the scenario database viewer from the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IIASA, 2014). Through the process of creating and testing their custom scenarios, users reflect their own values and views on how the policy issue could be solved, leading to a more interesting learning experience (Pidgeon et al., 2014).

Despite calls from many scientific communities, empirical evaluations of interactive web-tools are still relatively limited (Moss, 2016; Stellamanns et al., 2016; Trutnevyte et al., 2016; Wong-Parodi et al., 2014). Such evaluations may be critical for uncovering potential problems in the real use of these tools, as shown in more common evaluations of other information types, such as written communication or visualizations (Bosetti et al., 2017; Budescu et al., 2014; Canfield et al., 2017; Harold et al., 2016; Knoblauch et al., 2017; McMahon et al., 2015). In the case of interactive web-tools, most evaluations focused on the understanding and engagement of non-expert audiences. Wong-Parodi et al. (2014) suggested a framework for evaluating user comprehension in interactive decision aids and demonstrated it in a tool for coastal flooding. Mayer et al. (2014) and Pidgeon et al. (2014) reported high levels of user understanding and engagement with an interactive scenario-builder for exploring future energy systems. Bessette et al. (2016, 2014) also reported high knowledge gains in users of a similar tool that was embedded in a structured decision-making framework. Gong et al.

(2017) reported effects on user exploration strategies, when different types of modelling results were shown in a tool, e.g. scenarios vs. forecasts. Parker et al. (2015) showed that tools that summarized large databases of simulation-derived scenarios resulted in useful and understandable information for the users. Demski et al. (2017) found indications of preference anchoring, when exemplar scenarios were used in interactive scenario-builders. However, none of the above studies asked the very fundamental question whether the interactive web-tools perform better than the equivalent traditional formats, such as a report or a simple website, and hence justify the extra cost and effort to develop such interactive tools.

The few existing comparisons between interactive and static tools are inconclusive. Two studies on medical risk communication, Ancker et al. (2011) and Zikmund-Fischer et al. (2011), compared interactive and static pictographs (i.e. data representations with arrays of icons). While the first study detected no difference between the effects of the two graphics on understanding, the second one found indications of lower understanding and higher cognitive burden in the interactive condition. The last finding has also been identified in a study where users had to make trade-offs for land-use allocation (Arciniegas et al., 2013). On the other hand, a study on the adoption of energy-efficiency appliances showed that users using an interactive web-tool instead of educational slides were more effective in identifying the appliance with the lowest lifetime cost (Blasch et al., 2017). In the case of scenario-related tools, one nation-wide study for the Australian energy system found higher preference consistency using an online interactive scenario-builder than an information table (Jeanneret et al., 2014). Although the aforementioned study clearly commented on the users' understanding and engagement, it did not measure these factors quantitatively. Finally, in a study on Swiss electricity supply scenarios, we found similar satisfaction and self-reported understanding rates between an interactive electricity scenario-builder and static factsheets on paper (Volken et al., 2018).

Empirical evaluations are even scarcer on the role of the users' characteristics, such as demographics, skills or needs. Although it has been suggested many times that audience skills can enhance or limit the effectivity of interactive web-tools (Cohen and Hegarty, 2007; Harold et al., 2016; Spiegelhalter et al., 2011), only three aforementioned studies evaluated this. Both Ancker et al. (2011) and Zikmund-Fischer et al. (2011) studied numeracy; while the former study found indications that interactive web-graphics could alleviate numeracy problems, their finding was not reproduced in the latter. Blasch et al. (2017) studied a wide range of factors including age, education level and relevant literacy on energy-related investment. They found that higher education and literacy level positively correlated with identifying an appliance with lower lifetime cost, while the opposite was true for age. Nevertheless, they did not find any interaction between these factors and the tool's format. Web-related skills, although assumed important (Harold et al., 2016), have not yet been assessed. Similarly, there is no evaluation of whether users do get better customized information from interactive web-tools and whether this can support their needs in a better way than a non-customizable static output, such as a written document or a conventional static website.

2. Research questions and case study

In contrast to the growing number of interactive web-tools for outreach and education, two-way engagement, scientific research and decision support, there is little empirical evidence whether they can be more effective in comparison with a static medium. This is especially the case for interactive web-tools that allow users to build scenarios or explore large scenario databases. Although these tools are widely used for engaging non-expert users with complex issues, there have not yet been any empirical evaluation whether they can work better than traditional scenario techniques with a handful of static scenarios with narratives/storylines i.e. the so-called story-and-simulation approach (Alcamo, 2008; Trutnevyte et al., 2016). This study focuses on these scenario-related tools and aims to address the following questions:

1. How does an interactive web-tool with access to a large scenario database versus four static scenarios with storylines perform in making scenario information understandable, trustworthy and engaging for non-expert users?
2. How do the demographics, prior experience with the topic, numeracy, and website navigation skills of the users, influence this performance for each scenario format type?

As a case study, we chose to adapt an interactive web-tool Riskmeter (available at https://riskmeter.ch/) that we have developed in a recent study for understanding the preferences of an informed citizen panel in Switzerland for the Swiss electricity supply scenarios for 2035 and their environmental, health, and economic impacts (Volken et al., 2018). In Riskmeter, the users can explore a database of Swiss electricity scenarios for 2035, while making trade-offs between their environmental, health, and economic impacts and adhering to the technological constraints.

3. Methodology

3.1. Overall study design

In order to compare the interactive web-tool with the four static scenarios, an experimental approach was chosen. The format of scenario information was the sole experimental factor, resulting in a between-groups experiment with two experimental conditions: (1) the four scenarios condition and (2) the interactive web-tool condition. The experiment was implemented in the form of an online survey because in this way the personal context of user experience was kept (i.e. when users access such online web-tools by themselves). The survey started with a short introduction in the topic of the Swiss electricity supply and continued with questions related to the control variables of the study (Section 3.4). Participants were then randomly assigned to one of the two experimental conditions and received a link to a website that included either the interactive web-tool or four pre-selected scenarios (Section 3.2). A tutorial guiding participants in both websites was available but not obligatory. The participants were instructed to spend at least 2-3 minutes studying the information in the website and then to return to the survey to evaluate their experience with the website.

As shown in Table 1, we evaluated the two experimental groups in terms of (a) tested understanding, (b) self-reported understanding, (c) self-reported trust of information, (d) self-reported engagement, and (e) time spent in the website and drop-out rates. Our evaluation is based on frameworks used in previous conceptual and empirical evaluation studies of web-tools (Jeanneret et al., 2014; L. A. Mayer et al., 2014; Wong-Parodi et al., 2014; Zikmund-Fisher et al., 2011), although broader literature on user satisfaction exists too, e.g. (Violante and Vezzetti, 2017). Tested and self-reported understanding as well as tested and self-reported engagement are relatively common evaluation metrics. Trust has been only indirectly used in previous studies, although it can be affected by visualization characteristics (McInerny et al., 2014) and is part of frameworks and methodologies that assess information quality in general (Knight and Burn, 2005; Lee et al., 2002). More details on how dependent variables were measured are given in Section 3.3. The whole survey process is given in the form of a flow-chart in Figure 1.

Table 1. Dependent variables and their measurements

Dependent variables	Measurement	
	Self-reported	**Tested**
Understanding	Survey construct (6 items, 7-point Likert scale each)	True or False quiz on content (7 items, true/false/don't know)
Trust	Survey construct (7 items, 7-point Likert scale each)	-
Engagement	Survey construct (7 items, 7-point Likert scale each)	Time spent in website Drop-out rates

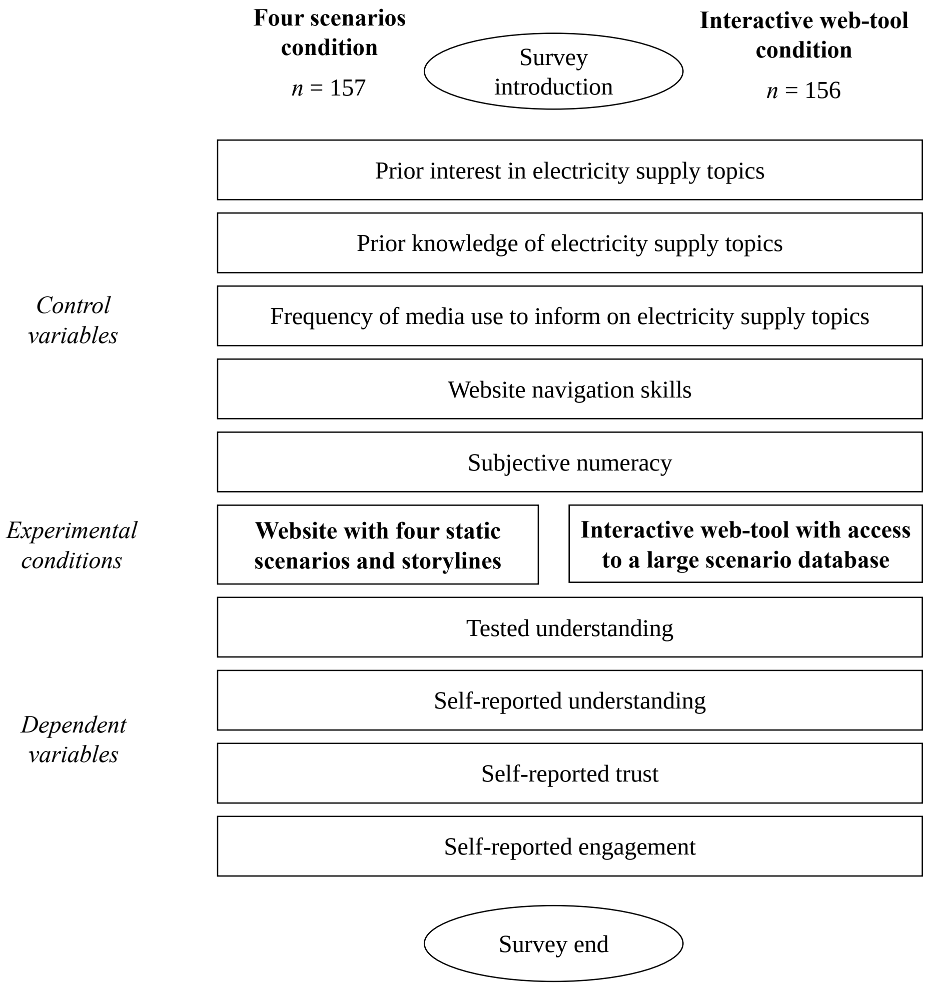


Figure 1. The flow-chart of the survey, showing all consecutive steps and the two experimental conditions. The dependent variables also include tested engagement, measured in the time spent in the website and the drop-out rates (see Section 3.3).

The survey and both web formats have been pretested with energy experts as well as 60 non-experts. These 60 individuals were only part of the pretesting and did not participate in the actual experiment. Based on the pretest feedback, we made several adjustments before launching the actual experiment. Additionally, as our materials were based on previous research, they have been already evaluated by other non-experts and a communication expert (Volken et al., 2018). The full survey script is available in the Supplementary Information (SI).

3.2. Experimental conditions

The interactive web-tool illustrated 13 electricity supply alternatives for Switzerland in 2035, their constraints and their environmental, health, and economic impacts. The alternatives included generation technologies that already exist or could be newly developed in Switzerland: large hydropower dams, large run-of-river hydropower, small hydropower, solar cells (photovoltaic), wind, deep geothermal, woody biomass, biogas, nuclear power, waste incineration, large natural gas power plants and net import from abroad. Electricity savings and efficiency improvements could also be chosen as an alternative to reduce the demand and the need for generation technologies. The choice of supply alternatives and their constraints were based on a previous energy modelling study that resulted in a large database of possible scenarios for the electricity supply in Switzerland 2035. (Berntsen and Trutnevyte, 2017). The assessment of environmental, health, and economic impacts were informed by two previous studies. Volken et al. (2017) used 12 semi-structured interviews in Switzerland in order to evaluate what non-experts knew and wanted to know about the various impacts of electricity generation. Volken et al. (Volken et al., 2018) then used color-coded factsheets with nine environmental, health, and economic impacts to elicit the informed preferences of the Swiss non-experts for electricity scenarios 2035. From these impacts, seven key impacts were chosen for this study and were quantified per TWh of supplied electricity using one or multiple indicators. The indicators' data were found in the literature, prioritizing sources that were closer to the context of the Swiss electricity system and, if possible, to the assessments for 2035. The chosen impacts and indicators included: (1) impacts on climate change, quantified in terms of $CO_{2\text{-eq}}$ (Bauer et al., 2017, 2012; Volkart et al., 2016); (2) local air pollution, quantified in terms of PM_{10eq}, SO_x and NO_x (Bauer et al., 2012; Masanet et al., 2013); (3) impacts on water, quantified in terms of water withdrawal and consumption (Fthenakis and Kim, 2010; Wernet et al., 2016); (4) impacts on landscape and land use, quantified in terms of m^2 of land use (Masanet et al., 2013; Maxim, 2014); (5) accidental impacts, quantified in terms of expected mortality and maximum fatalities in an accident (Volkart et al., 2016); (6) electricity costs, quantified in terms of Rp./kWh (BFE, 2016), and (7) electricity supply reliability, quantified in terms of three expert-derived metrics (Volkart et al., 2016), including autonomy (i.e. the degree to which the electricity supply chain is local), dispatchability (i.e. the degree to which the technology can supply electricity on demand) and equivalent availability factor (i.e. the degree to which a power plant is running at full capacity annually).

Through an interface of sliders (left panel of Figure 2), the users of the interactive web-tool controlled the utilization percentage of each alternative in TWh/year with the goal of covering the Swiss electricity demand of 70 TWh/year in 2035 (top center panel of Figure 2). The percentage extended from zero supply (0%) to the alternative's highest technical or resource potential for 2035 (100%) and could be moved in positions of 1% interval. For the existing generation technologies that would last until 2035, the slider was constrained to a minimum value equal to the supply that they are providing today. For all other alternatives and nuclear power (the Swiss Energy Strategy 2050 envisages gradual phase-out until 2035), the supply started at zero. For speed of interaction, the underlying model was kept simple: the contribution of each alternative in TWh/year was simply added to the total electricity supply. In this way, the interactive web-tool could create on the spot all possible combinations of supply alternatives given their constraints. The resulting process is equivalent to interactive web-tools querying a large database containing all these possible combinations. As in the publicly available Riskmeter version (https://riskmeter.ch/basic/), the web-tool showed immediate feedback per slider movement on seven impact categories (bottom right panel of Figure 2). Thermometers were used to visualize the impact values, where the rising temperature showed the impact severity that ranged from zero to the maximal value possible from the total set of scenarios in the web-tool.

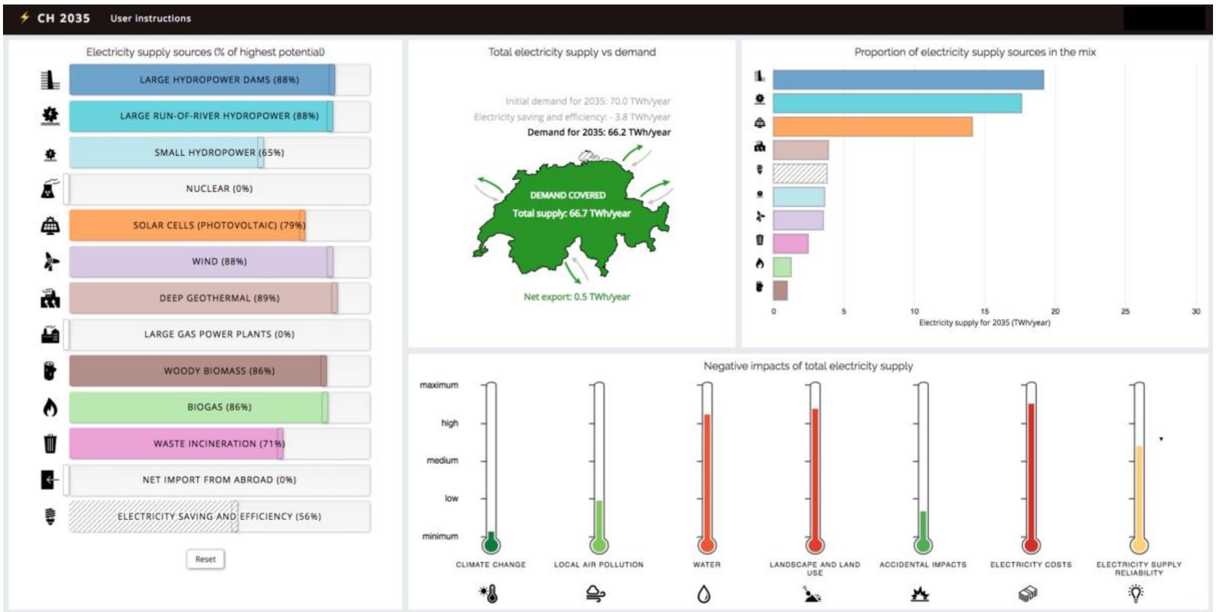


Figure 2. The interactive web-tool for exploring Swiss electricity supply scenarios for 2035 and related environmental, health, and economic impacts. The tool was adapted from the publicly available tool Riskmeter (https://riskmeter.ch/basic/)

The four static scenarios were selected following the typical storyline-and-simulation approach (Alcamo, 2008; Trutnevyte et al., 2016). The user could scroll down on the website and see four electricity supply scenarios with a title and a very short description (Figure 3). The scenarios were screenshots of the interactive web-tool, thus presenting exactly the same information and in visualizing this information in the same way. The selection of the scenarios was informed by existing scenarios for Switzerland (Berntsen and Trutnevyte, 2017; BFE, 2012; VSE, 2017, 2012) and intended to diversify the technologies and impacts presented by the four scenarios. The storylines along with details of each scenario can be found in the SI.

Figure 3. The website with four static electricity supply scenarios along with short introductory storylines. The numbering of the scenarios shows the order of the graphics and text in the website. Detailed, readable information about the storylines and the composition of the scenarios can be found in the SI.

3.3. Dependent variables

The dependent variables and their measurements are shown in Table 1. Tested understanding was measured through a content-based quiz with seven items, where participants needed to look up scenario information from the web-tool in order to answer "True" / "False" / "Don't know" to statements such as "The impact of electricity supply on local air pollution is low in any scenario". These quiz statements were carefully designed to be answerable by participants in both experimental conditions: participants in the four scenarios condition had to look across the four scenarios to find the answer, while participants in the interactive web-tool condition had to experiment with the sliders or create the test scenario mentioned in the statement in order to see if it was true or false. Self-reported understanding and all other self-reported variables were measured with seven items each on a seven-point Likert scale ranging from 1 = "totally disagree" to 7 = "totally agree". Most of these items were extended from previous studies (Jeanneret et al., 2014; Knight and Burn, 2005; Lee et al., 2002; L. A. Mayer et al., 2014; Wong-Parodi et al., 2014; Zikmund-Fisher et al., 2011). The internal reliabilities of the resulting scales were acceptable for self-reported understanding (Cronbach's α = .79, N = 6, after removing one scale item), good for self-reported trust (α = .84, N = 7), and excellent for self-reported engagement with the web-tool (α = .92, N = 7). The time spent in the website and the drop-out rates were measured only in the survey stages when participants were introduced to the web-tool and when they were using it for answering the quiz. SI includes the full survey.

3.4. Control variables

The control variables included demographics, questions on prior experience with the electricity supply topic and questions on skills related to the use of interactive web-tools (see SI for the survey). After the introduction, the survey included demographic questions on gender, age, highest education level and employment status. Next, the participants reported on their prior experience with the electricity supply topic, through two sets of seven items each on their interest and knowledge level; similar items were used in previous studies too (Fleishman et al., 2010; L. A. Mayer et al., 2014; ter Mors et al., 2013; Volken et al., 2018). The internal consistency was good for both the prior interest scale (α = .85, N = 7) and the prior knowledge scale (α = .86, N = 7). The participants also had to report how often they used seven media categories (e.g. newspapers, television, internet) for receiving information on the topic, using a seven-point Likert scale coded as 1 = "never" to 7 = "always" (α = .80, N = 7). The last section before the experimental part of the survey included two sets of five self-assessment items each on the participants' website navigation skills and subjective numeracy. The former was adapted from the Internet Skills Scale of Deursen et al. (2016) and reached acceptable internal consistency (α = .74, N = 5). The latter was adapted from the Subjective Numeracy Scale of Fagerlin et al. (2007) and achieved good internal consistency, but only after removing one scale item (final α = .82, N = 4).

3.5. Survey participants

In May 2018, we recruited 336 participants through an access panel in the German-speaking part of Switzerland. The access panel was designed to ensure that only non-experts can participate by excluding participants working or studying in the electricity or energy sector.

From the 336 completed responses to the survey, 23 were assessed as inattentive and were excluded if (a) they had unrealistically short answering times for the quiz for tested understanding (below one minute) and (b) if their answers to a set of five questions pairs, where each pair included a normal and a reversed-phrased version of the same content, were inconsistent. Participants ranged in age from 18 to 69 years (*M* = 43.75, *SD* = 13.99) and *n* = 160 (51.1%) self-reported as female. In terms of education, at least 42.8% of the participants have attained tertiary level of education (college or university), followed by 48.2% with secondary level (i.e. high school and vocational training) and 8.9% with primary level (obligatory education). The sample is thus almost representative of the Swiss population: it is slightly older than the Swiss average (*M* = 41.73 years), with a slightly higher female gender ratio (50.5%) and slightly more educated than the population (41.3% tertiary, 46.0% secondary and 12.7% primary education) (Eurostat, 2018; SFSO, 2016).

4. Results

4.1. Experimental check

The two experimental conditions were comparable in terms of all control variables as there were no statistically significant differences observed (Table 2). Both experimental groups on average reported moderate experience with electricity supply topics. Their prior interest in electricity topics scored slightly higher than the midpoint. The prior knowledge and the frequency of media use scored slightly lower than the midpoint. Website navigation skills and subjective numeracy were moderate-high in both groups with average scores well above the midpoint.

Table 2. Control variables by experimental condition

Control variables		Experimental conditions: Four scenarios with storylines (n = 157) *Count / M ± SD*	Experimental conditions: Interactive web-tool (n = 156) *Count / M ± SD*	Statistic
Gender *(count)*	Female	83	77	χ^2 = .385
	Male	74	79	
Highest education level *(count)*	Primary level	17	11	χ^2 = 1.558
	Secondary level	76	75	
	Tertiary level	64	70	
Age *(range: 18-69)*		44.10 ± 14.14	43.40 ± 13.87	t = .445
Prior interest in electricity supply topics *(score range: 7-49)*		29.91 ± 8.54	29.44 ± 7.66	t = .511
Prior knowledge of electricity supply topics *(score range: 7-49)*		26.99 ± 7.95	27.01 ± 7.87	t = -.021
Frequency of media use to inform on electricity supply topics *(score range: 7-49)*		26.54 ± 7.16	27.42 ± 6.82	t = -1.107
Website navigation skills *(score range: 5-35)*		24.90 ± 5.05	25.01 ± 4.99	t = -.202
Subjective numeracy *(score range: 4-28)*		21.38 ± 3.95	20.97 ± 4.50	t = .839

Note: No statistically significant differences between experimental conditions at $p < .05$. t-tests and *chi*-squared tests are used to calculate p-values. All statistics assume the four scenarios condition as the reference group. All survey items are available in the SI.

4.2. Non-experts using the interactive web-tool scored lower in tested understanding than the ones using four scenarios with storylines

As shown in Table 3, we found that non-experts using the interactive web-tool had, on average, less correct answers in the content-based understanding quiz than the ones using the four scenarios with storylines (t = 2.318, p = .021; $M_{interactive}$ = 3.54 vs. $M_{four\ scenarios}$ = 4.03 of correct answers out of the total 7). The "Don't know" answers in the quiz were used similarly between the two groups, suggesting that the format did not affect the ability of the participants to answer the quiz questions, but only reduced the accuracy rate. In order to further assess the quality of the participants' answers to the quiz, the average number of correct and wrong answers was compared to the number that would result from random guessing (i.e. the sum of correct and wrong answers per condition, divided by two). For both conditions, a statistically significant difference was found (four scenarios condition: $t = 9.148$, $p < .001$, $M_{correct} = 4.03$ vs. $M_{random} = 2.78$; interactive web-tool condition: $t = 4.248$, $p < .001$, $M_{correct} = 3.54$ vs. $M_{random} = 2.82$). This finding implies that most of the participants made a genuine effort to answer and performed better with any of the tools than with random guessing. When the effects of demographics, prior interest in the electricity subject, website navigation skills, and numeracy were controlled in a regression analysis, they did not significantly affect the results. This reinforced the notion that the format was a critical factor in the tested understanding quiz.

Looking at each quiz question separately, participants using the interactive web-tool performed worse in comparison with participants using the four scenarios with storylines in almost all of the quiz questions. These differences were statistically significant in three out of seven questions in total. This suggests that the effects of the interactive web-tool were not uniform across all questions and they may have depended on the complexity of each question. Overall, in our case, the interactive web-tool did not provide any benefit for understanding as compared to the website with four scenarios with storylines. SI introduces the results of the tested understanding per quiz question.

Table 3. Dependent variables by experimental condition

Dependent variables	Experimental conditions: Four scenarios with storylines (n = 157) *Count / M ± SD*	Interactive web-tool (n = 156) *Count / M ± SD*	Statistic
Understanding – tested *(score range: 0-7)*			
Correct answers	4.03 ± 1.99	3.54 ± 1.66	t = 2.318*
Wrong answers	1.57 ± 1.27	2.10 ± 1.26	t = -3.692**
Don't know answers	1.41 ± 2.05	1.36 ± 1.77	t = .224
Understanding – self-reported *(score range: 6-42)*	26.64 ± 5.50	25.88 ± 5.82	t = 1.195
Trust – self-reported *(score range: 7-49)*	32.56 ± 5.95	32.62 ± 6.04	t = -.090
Engagement – self-reported *(score range: 7-49)*	31.55 ± 8.36	31.76 ± 8.60	t = -.218
Engagement – tested			
Time spent in the website stage *(seconds)*	339 ± 273	366 ± 334	t = -.806
Drop-out rates in the website stage *(count)*	7	10	χ^2 = .504

Note: *p < .05; **p < .001. t-tests and chi-squared tests are used to calculate p-values. All statistics assume the four scenarios condition as the reference group. All survey items are available in the SI.

4.3. Performance was similar between the two groups in terms of self-reported understanding, trust, engagement and time spent in the website

In contrast to the tested understanding, all self-reported measures (self-reported understanding, engagement, and trust of the information) did not show any statistically significant difference between the two groups (Table 3). Both groups reported a more-than-average usability with all self-reported measures scoring statistically significantly above the midpoint (self-reported understanding: t = 4.253, p < .001, $M_{four\ scenarios}$ = 26.64 vs $M_{midpoint}$ = 24.00 for the four scenarios condition and t = 2.853, p = .005, $M_{interactive}$ = 25.88 vs $M_{midpoint}$ =

24.00 for the interactive web-tool condition; self-reported trust: $t = 6.790$, $p < .001$, $M_{four\ scenarios}$ = 32.56 vs $M_{midpoint}$ = 28.00 for the four scenarios condition and $t = 6.755$, $p < .001$, $M_{interactive}$ = 32.62 vs $M_{midpoint}$ = 28.00 for the interactive web-tool condition; self-reported engagement: $t = 3.762$, $p < .001$, $M_{four\ scenarios}$ = 31.55 vs $M_{midpoint}$ = 28.00 for the four scenarios condition and $t = 3.861$, $p < .001$, $M_{interactive}$ = 31.76 vs $M_{midpoint}$ = 28.00 for the interactive web-tool condition).

Similarly, there was some difference, but no statistically significant difference in time spent in the website and drop-out rates between the two experimental conditions. The average duration using the web-tools was around 5 minutes in the four scenarios condition and 6 minutes in the interactive web-tool condition. The average drop-out rates at the stage where participants see the interactive web-tool/four scenarios were 4% and 6%, respectively (the average drop-out rate for the whole survey was 14%). As before, running a regression analysis with the demographics and pre-experimental characteristics as covariates, did not significantly affect these results.

4.4. Website navigation skills, numeracy and prior experience with the subject had a positive correlation with understanding, trust and engagement

As shown in Table 4, there were statistically significant correlations in one or both of the groups between dependent variables and numeracy, website navigation skills and prior experience with the subject. All of these correlations were positive and their effect size ranged from low to moderate, suggesting that numeracy, website navigation skills and prior experience with the subject were beneficial but not critical for usability. Specifically, website navigation skills and numeracy correlated to tested understanding in both conditions, indicating that these skills were more-or-less important for answering the quiz questions (website navigation skills: $r_{\text{four scenarios}} = .32$, $p < .001$; $r_{\text{interactive}} = .21$, $p = .003$ / numeracy: $r_{\text{four scenarios}} = .22$, $p = .007$; $r_{\text{interactive}} = .16$, $p = .046$). A similar positive effect was found in the case of self-reported understanding, but only in the four scenarios condition (website navigation skills: $r_{\text{four scenarios}} = .26$, $p = .001$ / numeracy: $r_{\text{four scenarios}} = .19$, $p = .017$). In the interactive web-tool condition, self-reported understanding was significantly related to the prior interest and frequency of media use (prior interest: $r_{\text{interactive}} = .20$, $p = .011$ / frequency of media use: $r_{\text{interactive}} = .21$, $p = .008$), suggesting that participants that were feeling informed and interested in the subject felt more confident that they understand the information of the interactive web-tool. This confidence might have also affected self-reported trust as the trust was significantly related to the frequency of media use ($r_{\text{four scenarios}} = .18$, $p = .023$; $r_{\text{interactive}} = .21$, $p = .009$). Participants that were previously more engaged with the subject reported higher engagement with the tool in both conditions (prior interest: $r_{\text{four scenarios}} = .24$, $p = .002$; $r_{\text{interactive}} = .32$, $p < .001$ / prior knowledge: $r_{\text{interactive}} = .17$, $p = .029$ / frequency of media use: $r_{\text{four scenarios}} = .19$, $p = .016$; $r_{\text{interactive}} = .30$, $p < .001$) and spent more time with it in the interactive condition (prior interest: $r_{\text{interactive}} = .22$, $p = .006$). Numeracy also played a role in both conditions for self-reported trust ($r_{\text{four scenarios}} = .21$, $p = .008$; $r_{\text{interactive}} = .17$, $p = .033$) and engagement ($r_{\text{four scenarios}} = .19$, $p = .017$; $r_{\text{interactive}} = .19$, $p = .017$), suggesting that it can help in the overall usability of such tools, regardless of the format. On the contrary, website navigation skills affected self-reported trust ($r_{\text{four scenarios}} = .26$, $p = .001$) and time spent in the website ($r_{\text{four scenarios}} = .24$, $p = .003$) solely for the four scenarios condition, indicating that a possible moderation effect may have diminished the effects of these skills in the interactive web-tool condition. No statistically significant correlations have been observed between the demographics and the dependent variables, showing that even variables such as the age or education level of the participants did not have an effect.

Table 4. Correlations between the control and the dependent variables

Control variables	Understanding tested	Understanding self-reported	Trust self-reported	Engagement self-reported	Time spent in the website
	Dependent variables				
Point-biserial correlation	$r_{b,\text{four scenarios}}$ / $r_{b,\text{interactive}}$				
Gender	-.09 / .09	-.01 / .06	.02 / .09	-.07 / -.03	.05 / .04
Highest education level					
2^{nd} vs 1^{st}	-.10 / -.02	-.02 / .04	.01 / -.05	.06 / -.04	-.10 / -.02
2^{nd} vs 3^{rd}	.12 / .06	.01 / .08	-.01 / .07	-.06 / .04	.06 / -.02
Pearson's correlation	$r_{\text{four scenarios}}$ / $r_{\text{interactive}}$				
Age	.03 / -.04	-.14 / -.05	-.08 / .02	-.07 / -.01	.01 / .09
Prior interest in electricity supply topics	.07 / .05	.09 / .20*	.15 / .15	.24** / .32***	.04 / .22**
Prior knowledge of electricity supply topics	-.03 / .09	.03 / .13	.03 / .09	.12 / .17**	.01 / .05
Frequency of media use to inform on electricity supply topics	.11 / .05	.10 / .21**	.18* / .21**	.19* / .30***	.09 / -.08
Website navigation skills	.32*** / .21**	.26** / .02	.26** / .10	.15 / .04	.24** / .02
Subjective numeracy	.22** / .16*	.19* / .13	.21** / .17*	.19* / .19*	.14 / .02

**p* < .05; ***p* < .01; ****p* < .001. Significance (two-tailed) is based on a 1000 bootstrap samples – BCa

Although most of the correlation coefficients differed between the experimental conditions, these differences were statistically significant only for the case of website navigation skills and their correlation with self-reported understanding ($r_{\text{four scenarios}} = .26$ vs $r_{\text{interactive}} = .02$, $z_{\text{difference}} = 2.128$, $p = .033$). A further moderation and simple slope analysis showed that, for the four scenarios condition, there is a significant positive relationship between website navigation skills and self-reported understanding ($b = 0.28$, 95% CI [−0.12, 0.44], $t = 3.558$, $p < 0.001$). This emphasizes the importance of website navigation skills in understanding and further suggests that another factor might have dampened their effects in the interactive web-tool condition.

In order to assess if the combination of format and the control variables can sufficiently predict the performance in both conditions, regression models were created for each of the dependent variables (tested understanding, self-reported understanding, self-reported trust, self-reported engagement and time spent in the website) using the control variables and the format as predictors (gender, age, highest education level, prior interest, prior knowledge, frequency of media use, website navigation skills, numeracy, format). The resulting standardized regression coefficients revealed similar effects to the correlation coefficients of Table 4. For example, the website navigation skills were significant predictors of the tested understanding (*Beta* = 0.24, $p < .001$) and the prior interest in the electricity subject was a significant predictor of the self-reported engagement (*Beta* = 0.36, $p < .001$). However, the R^2 was low for all regression models (tested understanding: $R^2 = .11$, $F = 3.88$, $p < .001$; self-reported understanding: $R^2 = .09$, $F = 2.96$, $p = .001$; self-reported trust: $R^2 = .10$, $F = 3.58$, $p < .001$; self-reported engagement: $R^2 = .15$, $F = 5.11$, $p < .001$; time spend in the website: $R^2 = .05$, $F = 1.60$, $p = .107$). This suggests that the regression models could not explain a large part of the model variance, but they still supported our previous findings. Due to the low variance explained, detailed regressions results are not reported.

5. Discussion

Our first, thought-provoking finding is that participants in the four scenarios condition performed better than participants in the interactive web-tool condition in terms of tested understanding. Participants appeared to use the information on electricity supply alternatives and environmental, health, and economic impacts more effectively when having four scenarios with storylines in order to answer the content-based understanding quiz. A reason for this difference may be related to the method of looking for information. In the interactive web-tool condition, the participants had to actively create scenarios to test the validity of the quiz questions, while in the four scenarios condition, participants needed to look up information from only four given scenarios. It is probable that the active way of looking for information in the interactive web-tool have led to higher cognitive effort that in turn reduced the performance in answering understanding quiz. Past evaluation studies also pinpointed the cognitive burden as an issue in tasks involving information comprehension for interactive tools online (Bessette et al., 2016; Zikmund-Fisher et al., 2011) or in workshops (Arciniegas et al., 2013). Although counter-examples exist in the literature (i.e. where interactive tools supported understanding), two factors could have led to different results than in our study: (a) the participants had studied the information included in the previous interactive web-tools at least for a few hours prior to evaluation (L. A. Mayer et al., 2014; Volken et al., 2018) and (b) a less complex task with one to two objectives was given (Blasch et al., 2017; Jeanneret et al., 2014). In our case, the limited average time spent in learning how to use the interactive web-tool and actually using it (5-6 minutes) along with the complexity of matching 13 technologies with seven impacts, might led to a disadvantage for the interactive web-tool condition. This argument is supported by the moderate correlations found between time spent and both tested and self-reported understanding (for tested: $r_{four\ scenarios}$ = .365, p < .001, $r_{interactive}$ = .289, p < .001; for self-reported: $r_{four\ scenarios}$ = .372, p < .001, $r_{interactive}$ = .382, p < .001). Another factor may be that participant attention became even more fragile by the information “synchronicity” in the interactive web-tool: when the user moves one slider, information about the electricity demand-supply relation and the severity of seven impacts is shown directly. Such simultaneous feedback can help with tradeoff-making but may also lead to an overload of information on diverse and sometimes conflicting objectives. Nonetheless, our findings suggest that scenario-related tools, such as our interactive web-tool, should not be developed with an assumption that they will definitely lead to a better understanding and knowledge of the users.

The second main finding is that the interactive web-tool and the website with four scenarios with storylines had very similar performance in self-reported measures of understanding, trust and engagement. In terms of self-reported trust, this result was also expected even if, as far as we are aware, it was tested for the first time. People usually perceive the information as reliable if they believe its source is reliable (Knight and Burn, 2005) and if its format is adequately designed (McInerny et al., 2014). Both of our experimental conditions came from the same source and had seemingly similar design. In terms of engagement and understanding, this was also found in our previous workshop study with the same topic, where participants reported similar satisfaction and learning experience for paper factsheets and an interactive web-tool (Volken et al., 2018). For self-reported engagement, other previous studies have suggested that interactive web-tools can have a positive effect (L. A. Mayer et al., 2014; Pidgeon et al., 2014), but these studies did not compare the tools with static equivalents. In our case, it might be again the short use of time and the complex task that did not allow the interactive web-tool condition to outperform the four scenarios condition. The lack of time and task’s complexity could have also increased participant stress, as it was also found in a previous empirical study (Bessette et al., 2016), and that stress may have further reduced engagement (McInerny et al., 2014). Another reason limiting engagement in the interactive web-tool condition might be that participants had to create scenarios to answer the quiz, while participants in the four scenarios condition directly received four scenarios with simple but clear narratives. We designed the quiz questions to serve as motivation for the participants of the interactive web-tool condition to discover the tool capabilities, but this might not have been enough to overcome the cognitive load and the average prior interest in the subject. Instead, the statistically significant correlation between prior interest and engagement in the interactive web-tool indicated that participants that were already interested in the subject were also more engaged with the tool. A further moderation analysis showed that the interactive web-tool did not engage low interest participants more than the four scenarios. In conclusion, we do not find evidence for superiority of an interactive web-tool with access to a large scenario database over a website with four scenarios with storylines in terms of self-reported understanding, trust and engagement.

In the case of understanding, the self-reported measure contradicts the tested one: there was no statistically significant difference between the conditions in terms of self-reported understanding, while in fact the participants of the four scenarios condition performed better in the content-based quiz. Disparities between self-reported and tested measures were also found in previous studies (Arciniegas et al., 2013; Bessette et al., 2016, 2014). In our case, a possible explanation could be found in the subject of the tool: since the debate on the future of the Swiss electricity system goes on for several years now, the participants might have believed that they more or less already understand the electricity subject (Volken et al., 2018). The prior knowledge of the electricity subject that was reported in our sample as close to the midpoint on average seems to go towards this direction. Nevertheless, awareness gaps in the electricity subject have been observed in a past study in Switzerland (Volken et al., 2017). It is thus possible that the participants used the interactive web-tool to look for the answers, but due to the cognitive load and limited time they reverted—possibly without realizing it—to their prior knowledge. Prior attitudes, such as the affect to certain electricity supply technologies, might have also interfered with the scenario building task in the interactive web-tool condition (Jobin and Siegrist, 2018). Cognitive studies in graphic comprehension accentuate the importance of matching the graphic with the viewer's knowledge, goal or visuospatial ability (Harold et al., 2016). The lack of such a matching might also partly explain the disparity in our case.

The third finding is that the website navigation skills, numeracy and prior experience with electricity supply topics have some–but not decisive–effects on the usability performance. Participants with high website navigation skills and numeracy performed better in the quiz for tested understanding in both experimental conditions. Such a finding is in line with the statements in literature that the appropriate skills are helpful to use interactive and static tools effectively (Harold et al., 2016). At the same time, the low-to-moderate size of the correlation coefficients showed that lower website navigation skills and numeracy are not restrictive for understanding the information in these tools. The same effect of the role of website navigation skills and numeracy was found for self-reported understanding in the four scenarios condition but, surprisingly, not in the interactive web-tool condition. This might correspond to a previous finding where interactive graphics alleviated numeracy differences in risk perception, thus diminishing the effect of these skills in the interactive condition (Ancker et al., 2011). Other factors for this reduced effect might be the aforementioned cognitive burden and anxiety in the interactive web-tool condition These factors could also explain why a similar effect was found solely in the four scenarios condition, where website navigation skills correlate with self-reported trust and time spent in the website. On the contrary, high prior interest, knowledge and frequency of media use to inform on electricity supply topics favored the participants of the interactive web-tool condition and led to higher correlations with self-reported understanding, time spent and self-reported engagement. This finding could indicate the that interactive web-tool was perceived better by "experienced" participants on the subject, although none of the correlation coefficients differed significantly between the conditions. However, there was no effect of prior interest, knowledge and frequency of media use on tested understanding in any condition, unlike the positive correlations found by Blasch et al. (2017). This indicates that our interactive web-tool was not disadvantaging less-experienced participants to answer the quiz of tested understanding. In contrast again to Blasch et al. (2017), we found no statistically significant correlation of gender, age and education level with the performance. This difference in findings could be due to the fact that Blasch et al. (2017) used much higher sample sizes (one sample with N = 916 and another with N = 5,015) and a task with lower complexity and number of parameters.

There are some limitations in our study, mainly related with the design of the experiment. First of all, we intentionally did not include a decision or preference task in order to focus on the effectiveness and usability of the tools for education and outreach purposes. This might have negatively affected the engagement and attention of the participants, regardless of our efforts to motivate them to discover the tool by asking them to answer the quiz questions. Similarly, the large number of technologies and impacts may have reduced comprehension regardless of the format. Especially for the interactive web-tool, the simultaneous presentation of so many parameters might have further increased cognitive load. These effects were considered in the experiment's design phase and could have been studied by developing a version of the tool with less parameters and another one that allowed the users to select and submit a preferred scenario (see e.g. Volken et al. (2018)). Another limitation is that we did not record how the participants interact with the tools, e.g. using mouse tracking. This method would not have altered our current findings, but it would have given a more detailed insight in what sliders the participants used in the interactive web-tool etc. Finally, we could have also used gaming features to increase engagement or, as it became apparent by the limited fit in the regression analyses, we could have looked at other factors such as visuospatial skills. All the above limitations should be addressed in the future research and can possibly clarify some of the effects we found.

6. Conclusions

Interactive web-tools have many claimed benefits of increasing understanding and engagement for the purposes of outreach and education, two-way public engagement, scientific research on eliciting preferences and decision support. In this study, an interactive web-tool for non-experts with access to a large ensemble of Swiss electricity supply scenarios to 2035 was assessed in comparison to a website with four static scenarios with storylines. Our interactive web-tool performed just as well in terms of self-reported understanding, engagement, and trust of the participants as the website with the four scenarios with storylines. Even more, the interactive web-tool did not lead to a measurable advantage over the more traditional website that presented four pre-selected scenarios with short storylines/narratives. In fact, we found that the interactive web-tool could have even reduced comprehension of the information because the participants in the interactive web-tool condition scored statistically significantly worse than the participants in the four scenarios condition in a quiz that required to extract information from the scenarios. A possible explanation for such a reduced performance in the interactive web-tool condition is the higher cognitive load that is required for looking up the information and receiving simultaneous feedback over multiple parameters. In both conditions, we found a low-to-moderate correlation of website navigation skills and numeracy with tested understanding, suggesting that these skills are important but not imperative. Participants with higher prior experience with electricity supply topics were also more engaged in both conditions, while demographics did not have any effect. Although the effects of the control variables varied between the conditions, only one statistically significant difference was found: high website navigation skills increased self-reported understanding in the four scenarios condition but not in the interactive web-tool condition. This suggests that another factor might have moderated the effects of these skills in the interactive web-tool condition, such as a possible overload of information from the interactive web-tool.

As our interactive web-tool was modelled after similar tools found online, the results may provide a word of caution and a call for more frequent empirical evaluations of existing and future tools. The results of our study indicate that interactive web-tools may not automatically bring benefits to any scenario application. Since such tools usually require more time and effort to develop, it is important to assess whether and when such tools really offer a benefit or are necessary. Even with rigorous development of such tools, there might be cases where simpler and more pragmatic approaches, such as conventional websites or written factsheets, would work equally good or even better. For environmental scenario studies that aim to incorporate interactivity to explore scenario databases, it is also worth to investigate the combination of methods, e.g. guiding the users first through diverse example narratives/scenarios and then through scenario-building in an interactive way. In any case, continuous evaluation in all stages of development and deployment of interactive web-tools is necessary in order to assure that they fulfill the goals they are built for.

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