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Combining a conjoint experiment and machine learning model to include end-users in a constructive technology assessment: The case of seasonal thermal energy storage☆

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ABSTRACT

By definition, the mapping of technological development occurs in the context of uncertainty and with a risk of failure. Decisions taken at the onset of the development phase are significant because the technology has not reached the market yet. The technology loses its malleability during the development phase because of entrenchment. Thus, the objective of a constructive technological assessment is to embed social aspects – additional perspectives – in the context of technological developments. In line with extant literature, a pivotal perspective is the (future) end-user of the technology. Hence, market acceptance remains a constraining factor in technological development, notably for renewable energy technology. However, existing studies have not included (future) end-users in development phases. They have always taken place after the technology has reached the market.

To bring technological development and market acceptance closer, this study develops an innovative method that combines a conjoint experiment with a supervised machine learning model to predict the behavioural intention of end-users to accept a new (energy) technology. This study illustrates the proposed methodology through a conjoint experiment on seasonal thermal energy storage. The ML model uses input from a survey with a conjoint experiment to predict end-users' market acceptance. With N = 12,096 (1008 participants exposed to 6 x 2 conjoint tasks), the ML model predicts behavioural intention with an accuracy of RMSE = 1.55 on a 10-point scale. The model is then used to predict hypothetical acceptance from mock end-users' profiles and varying technological features. Thus, this study opens new perspectives for constructive technology assessment and conjoint experiment literature, and furthers discussions on social acceptance of energy technologies.

1. Introduction

The urgent need to mitigate the threat of anthropogenic climate change is, in most cases, no longer debated. Ensuring affordable and renewable energy production and consumption is a pressing global challenge. Despite the pressure for each country to develop significantly more renewable energy infrastructures, meeting the ambitious global environmental goals comes with uncertainty and a risk of failure (Upham, Oltra, & Boso, 2015). Scholars have acknowledged that innovation and cutting-edge (energy) technologies have a significant potential to mitigate climate change and bolster sustainable development (Al-Emran, 2023; Dogan, Ghosh, Hoang, & Chu, 2021; Svarc & Dabic, 2022) Although it is irrefutable that scientific and technological innovations in developing renewable energy production are a must, the resolution of climate change also hinges on social acceptance and, more specifically, on the market and community acceptance of these innovations (Yamame & Kaneko, 2023). In other words, social acceptance remains a barrier that regularly impedes the installation and operation of renewable energy infrastructures both at the community and individual levels (for a review, see Batel 2019, Milani, Dessi, and Bonaiuto 2024, Segreto et al. 2023).

In their seminal paper, Wüstenhagen, Wolsink, and Bürer (2007) defined the first cornerstone of contemporary research on the social acceptance of renewable energy technology (RET). They examined the socio-psychological, community and market factors that contribute to or hinder acceptance. In parallel, Huijts, Molien, and Steg (2012) have designed the technology acceptance framework (TAF) that builds upon

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the technology acceptance model (TAM) (Venkatesh & Davis, 1996). Recent additional models extended this research to the case of energy technology with, for example, an integrated sustainable energy technology adoption model (i-SETA) (Bonaiuto et al., 2024). The objective of these models has been to explain the acceptance of (renewable) energy technology. These models provide an encompassing perspective on the constraining factors – for example, perception, affect, social norms, or knowledge – that increase or decrease the behavioural intention to accept an RET. In brief, these constraining factors have been impeding countries from reaching their energy targets, with renewable energy remaining marginal in their energy mix (Dermont, Ingold, Kammermann, & Stadelmann-Steffen, 2017). Recent research has confirmed that three types of factors constrain the social acceptance of an (energy) technology: technological features and contextual and personal factors (for a review, see Milani et al. 2024).

However, literature on social acceptance in the broad population have always taken place after the RET has reached the market. In other words, the undesirable failure of RET acceptance is acted upon when the technology is already a marketable product.[1] At this stage, the RET is mature and room for technical modifications is tiny or even nonexistent (Versteeg, Baumann, Weil, & Moniz, 2017). On the contrary, decisions taken at the onset of the development phase are decisive because the technology has not reached the market yet and, thus, is still malleable. Though social acceptance scholars reach conclusions and make recommendations, it is too late because the development phase is over. This implies that irreversibilities have taken place due to the enactors' decision, i.e., entrenchment (van Merkerk & van Lente, 2005).

In line with (Kadenic et al., 2024), the main objective of this article is to apply a proactive, rather than an ex-post, examination of the social acceptance of an (energy) technology. Social acceptance should be explored before the technology diffusion in the market in order to increase the adoption of the technology. Constructive technology assessment (CTA) literature states that social aspects, notably (future) end-users' perspectives, should be embedded in the technological development process to prevent the future failure of technology acceptance. Such a mismatch between studies on social acceptance taking place after the RET reaches the market and the loss of technological malleability once the technology is mature confirms that the technological development of the RET and research on social acceptance have remained two separate areas.

Bearing this in mind, this study aims to bring technological development and technology/social acceptance closer. It builds upon existing research on social acceptance of the RET that has recently been prominently applying conjoint experiments in its methodological approach (e.g. Stadelmann-Steffen & Dermont, 2021 or Vuichard, Broughel, Wüstenhagen, Tabi, & Knauf, 2022). Indeed, a conjoint experiment is a promising methodological approach for revealing participants' multidimensional decision preferences, although they have only little (or no) information and knowledge related to the RET at stake (Kubli, 2021; Vuichard et al., 2022). Nevertheless, this study goes a step further by using data from a conjoint experiment with a supervised machine learning (ML) model with ordinary least square (OLS) regression. Combining a rating-based conjoint experiment with a supervised ML model, this paper develops an innovative method to predict the market acceptance of (future) end-users of (renewable) energy technologies that remain in their early phase of development. This contributes to a CTA by predicting market acceptance for end-users and anticipating the risk of failure.

A conjoint experiment for an RET answers the following fundamental question: Is a technological factor of any significance for acceptance given other technological factors? In the existing literature, average marginal effects (AMCEs) and marginal means (MMs) have remained the most popular outcomes of conjoint experiments among social scientists. Both computational approaches display the mean outcomes averaged over the distribution of other factors and over the responses of other participants. However, they fail to account for individual-level predispositions and attitudes – that is, external variables – that either directly influence the decision preferences or interact with technological factors. Although a conjoint analysis can present subgroup analyses, it cannot capture the direct or interacting influence of individual-level factors on technological acceptance. That being said, technology acceptance is a multidimensional decision preference that not only rests upon the features of the technology itself but also on the individual-level attitudes and predispositions.

In agreement with Chapelle and Harchaoui (2004), Toubia, Evgeniou, and Hauser (2007) and Ham, Imai, and Janson (2024), this study assumes that the application of a supervised ML model shows considerable potential for improving the predictive ability of conjoint experiments. A conjoint experiment is a learning problem that can be cast as a classification task in which participants accept or reject the technology y from the basket with k questions, or as a regression task with participants rating different technologies y from the basket. Thus, this study combines the strengths of a conjoint model with the predictive power of ML.

The proposed methodology is illustrated with a conjoint experiment on seasonal thermal energy storage (STES). This energy technology presents as an ideal case to measure social acceptance before an RET reaches the market. Not only are most STES technologies not sufficiently mature yet and remain malleable (Yang, Kramer, & Sun, 2021) but STES is also a potentially pivotal technology in the energy transition because seasonality is an inherent feature of the energy system (McKenna, Fehrenbach, & Merkel, 2019; Shah, Aye, & Rismanchi, 2018). This study begins with the TAF given by Huijts et al. (2012) and combines a conjoint experiment with a supervised ML model. First, the rating-based conjoint experiment benefits from an online cross-section survey in Switzerland (N = 1008). The survey and the conjoint experiment have been designed with a team of energy engineers with expertise in STES. This iterative and interdisciplinary approach ensured the technical validity of the experiment while also simplifying the content to make it understandable for laypeople. Considering that each participant revealed their preferences on 6×2 tasks, this article develops a supervised ML model on n = 12'096 observations. Second, it fits a supervised ML model with OLS regression with not only the technological features from the conjoint experiment, but also the individual-level predispositions and attitudes, i.e., input variables. The ML model learns from these inputs to obtain a function that accurately predicts the output which is the behavioural intention to install the STES technology, when presented with new input data. In the case of STES, the ML model can predict the behavioural intention to install the energy technology with a RMSE of 1.55 for the test dataset (on a 10-point scale).

Although the accuracy of this specific ML model for STES acceptance remains questionable, the strength of this contribution is to confirm that the innovative method to combine a conjoint experiment with ML is working and can be applied to other (energy) technology in the development phase. This method is the first to measure market acceptance of (future) end-users in the early phase of technological development. As already mentioned, a CTA must include a broad range of stakeholders – that is, the society – in the development phase (Schot & Rip, 1996). Facing a conjoint experiment (future) end-users can, with

[1] This article acknowledges recent studies on the acceptance of experimental energy technologies, such as geoengineering, negative emissions, or the management of solar radiations (Sovacool, Baum, & Low, 2022a, 2022b). Kadenic, Ballantine, Olsen, Enevoldsen, and Gross (2024) also synthesises factors influencing stakeholders' acceptance of chemical solar energy storage, which is a technology that is not on the market yet. Nevertheless, these studies examined social acceptance either with expert surveys or interviews, but did not evaluate the social acceptance of (future) end-users or only conducted a literature review rather than gathering empirical data.

sufficient information, shape a positive or negative affect; form a perception of the risks, costs, and benefits; and evaluate their preferences regarding the technology. The early inclusion of (future) technology users is beneficial because the energy technology is still malleable in this phase. Energy engineers can test the combination of technological features with individual-level attitudes and predispositions to assess which one garners the highest market acceptance. Combining a conjoint experiment with a supervised ML model, (energy) technology developers can include the society in CTA to predict end-users' behavioural intention to accept or reject a technology. This iterative and interdisciplinary method is a step forward to bringing social science and technology developers closer together to overcome social acceptance barriers.

2. Theory and literature review

This section discusses theoretical concepts and models that are pivotal to the acceptance of RET. First, it elaborates on the TAM and the TAF. Second, it discusses the literature on the social acceptance of RET. This leads to a focus on a CTA, which serves as a roadmap to include behavioural intention to accept an RET earlier in the technological development phase.

2.1. Behavioural intention and technology acceptance

To begin with, it is seminal to separate the overlapping constructs of acceptability, acceptance, and adoption to determine an univocal definition of acceptance for this article. In their article, Bertsch, Hall, Weinhardt, and Fichtner (2016) explain that acceptability and acceptance are often used synonymously. However, they clarify that the term acceptability refers to the rational and reasonable judgments of experts on the technology. Bonaiuto et al. (2024) define acceptability as a favourable or unfavourable attitude towards a given (energy) technology on a negative-positive scale. On the other hand, acceptance discounts rational and reasonable judgments. It is defined as a measurement of a positive or negative behavioural intention of accepting an (energy) technology by the stakeholders. In other words, it measures the subjective readiness to accept a technology (Bertsch et al., 2016; Bonaiuto et al., 2024; Upham et al., 2015). It considers implementation in a neighbourhood, or market buying. A last step is then the adoption that refers to the actual diffusion of the (energy) technology (Bonaiuto et al., 2024). In this article, the definition of (energy) technology acceptance aligns with that of Bertsch et al. (2016) and Bonaiuto et al. (2024), who consider acceptance as a subjective behavioural attitude towards a given technology. This definition is a self-reported measurement of the readiness to install or support a given energy storage technology.

The vast majority of TAMs have highlighted the role of perception on behavioural intention to accept new technologies. In its seminal work, Davis (1985) suggested a TAM to explain the failure of technology adoption. This model is built upon the theory of reasoned action (TRA) (Ajzen & Fishbein, 1980) and the theory of planned behaviour (TPB) (Ajzen, 1991). It considers that the actual acceptance of a technology is driven by a user's motivation to accept – that is, use – this technology. This motivation is driven by two psychological constructs related to perception: *perceived usefulness* and *perceived ease of use* (Davis, Bagozzi, & Warshaw, 1989). First, perceived usefulness matches how useful or beneficial a technology could be for a user or the society as a whole. Second, perceived ease of use indicates how easy it is to use or implement the technology itself. In the original models, these two perceptions were hypothesised to be influenced by the features of the technology and assumed to have a direct impact on the attitude towards using the technology. However, in their final proposal, Venkatesh and Davis (1996) concluded that (1) perceived usefulness and perceived ease of use have a direct impact on behavioural intentions rather than on the attitude towards using the technology; and (2) perceived usefulness and perceived ease of use were not only influenced by the features of the technology but also by other considerations and factors, such as users' participation or nature of the implementation process. Consequently, they fine-tuned their model and opted for a more encompassing term to define the direct impact on user's perception: *external variables*. For years, this TAM model has remained the leading model in predicting technology acceptance.

Extending this literature to renewable energy technology, Huijts et al. (2012) presented the TAF. In this model, they emphasised the behaviour towards the technology. Huijts et al. (2012) consider that the intention to accept is driven by three factors: behavioural intention, social norms, and perceived ease of use. First, Huijts et al. (2012) also distinguish between acceptability which refers to the favourable attitude towards a technology, and acceptance which measures the deliberate positive behavioural intention or readiness to accept a technology. Behavioural intention is defined as the user's expectations regarding the use of the technology—that is, how *good* or *bad* the outcome will be for the user and society as a whole. This outcome is a weighing of positive and negative affects and perception of the technology—that is, perceived costs, perceived benefits, and perceived risks. This aligns with the construct of 'acceptability' (e.g. see Bonaiuto et al. 2024) Second, social norms refer to the influence of the social environment – that is, peers – on the user's behavioural intention. This additional factor has been derived from the TPB. The TPB assumes that the intention to use a technology is also driven by subjective norms—that is, perceptions of how the social environment will endorse the system. Third, perceived ease of use is in line with the TAM. Going a step further, the TAF hypothesises that the behavioural intention is motivated not only by the technology itself – that is, the technological features of TAM – but also by contextual factors (Huitjs, Molien, & van Wee, 2014). Therefore, the TAF included three psychological constructs: trust, procedural fairness, and distributive fairness; these psychological constructs have either a direct or indirect impact, through affect and perception, on behavioural intention.[2] Finally, Huijts et al. (2012) added that knowledge and experience of the technology are also mediating variables in this model.

To summarise, and considering both the TAM and TAF, the acceptance of a technology is not only driven by multiple constraining factors – *perception* and *affect* – associated with the technology but also by *contextual factors*, *external variables*, and *social norms*. These factors can directly or indirectly encourage or hamper the acceptance of the technology.

2.2. Social acceptance of renewable energy technologies

With the urgent need to fight climate change, a vast literature on the social acceptance of renewable energy technologies (RETs) has developed – in parallel to literature on technology acceptance – in social science. This literature underscores that technology enactors should not only concentrate on the development of adaptation or mitigating energy technologies but also examine their social acceptance with the aim of either reducing opposition or facilitating adoption (Milani et al., 2024) In a pioneering article, Sovacool (2014) concluded that disciplines related to social sciences are overlooked and unvalued in the energy research agenda. The article highlighted the potential for the field of energy research to 'expand methodologically and topically' (Sovacool, 2014, p.25) to reach other disciplines and vice versa. This recent literature trend appears complementary to research related to technology acceptance because it not only considers the multidimensional factors that influence acceptance but also indicates

[2] It is worth noting that procedural and distributive fairness aligns with the literature on community acceptance of an RET that emphasises the role of procedural and distributional justice (e.g. see Vuichard et al. (2022)).

the different types of acceptance. As a reminder, this article defines (energy) technology acceptance as the negative or positive behavioural intention to accept a technology—that is, the subjective readiness to accept a given technology (Bertsch et al., 2016; Bonaiuto et al., 2024).

It must be noted that this article follows Wüstenhagen et al. (2007), who isolated three dimensions of the social acceptance of RET: sociopolitical, community, and market acceptance. First, sociopolitical acceptance encompasses the more general level of acceptance of RET. Over the years, and with climate change reaching the top of political agenda-setting, the population progressively set its mind in favour of RET. Existing literature has confirmed that the sociopolitical acceptance of RET, in general, is more or less a given (for a review see Batel 2019, Segreto et al. 2023). However, this does not automatically translate into a behavioural intention to accept an RET at the community or market levels (Aitken, 2010; Batel, Devine-Wright, & Tangeland, 2013; Bell, Gray, Haggett, & Swaffield, 2013). Second, community acceptance stands for the concrete acceptance by residents and authorities of the site of an RET infrastructure in their neighbourhood. It can be said that this dimension of acceptance is an extension of the relevant but criticised Not In My Backyard (NIMBY) literature (Wolsink, 2006). The term NIMBY characterises public opposition to the implementation of an undesirable infrastructure at the local level, notably energy infrastructure, but support at the general level (Devine-Wright, 2009). To explain local opposition to infrastructure, a deterministic view of human psychology has been applied in empirical literature, considering that opposition is driven by physical proximity (for a review see Devine-Wright 2005). However, Wolsink (2006) questioned the reasoning behind this theory. He indicated that the NIMBY umbrella represents a constellation of attitudes that goes beyond the single explanation of physical proximity. Recent literature demonstrated that community acceptance is also strongly driven by political processes. For example, Vuichard et al. (2022) demonstrated how the distribution of costs and benefits among residents and institutions – that is, distributional justice – and how the inclusion of residents in the decision-making process – that is, procedural justice – is of significance for community acceptance. Third, market acceptance highlights the actual market adoption of RET. It measures the extent to which individuals are willing to install RET. In brief, this study agrees with existing literature that has demonstrated that market and community acceptance remain pivotal challenges in the implementation stage (Stadelmann-Steffen & Eder, 2020; Sütterlin & Siegrist, 2017).

Literature has also pinpointed that social acceptance is a multidimensional choice. This also aligns with the previously mentioned technology acceptance models, i.e., TAM and TAF. Stadelmann-Steffen and Dermont (2021) stated that individuals approve certain aspects of an RET technology while rejecting others. Thus, a weighing of pros and cons of different factors ranging from technical, political, and social perspectives comes into play for individuals, who also have their own attitudes and predispositions when deciding upon supporting or installing an RET infrastructure (e.g. see Boudet 2019, Dwyer and Bidwell 2019, Strantzali and Aravossis 2016, Vuichard et al. 2022, Vuichard, Stauch, and Dällenbach 2019, Walker and Baxter 2017).

In a recent comprehensive meta-analysis, Milani et al. (2024) concluded that acceptability, acceptance, and adoption are driven or hindered by beliefs related to the technological features, the context (e.g. policy regulations or market considerations), and personal factors. This meta-analysis highlighted research on the role of contextual and general psychological factors in social acceptance. For example, Ellis, Barry, and Robinson (2007) emphasised three different factors that influence the social acceptance of RET. First, the technology itself carries a certain level of acceptance or rejection. For example, solar PVs, wind turbines, hydropower, battery storage, or hydrogen do not begin the road to acceptance at the same stage. Some might be hindered by a negative perception, while others may profit from a positive overall perception. This depends on their technological features and their technological maturity. Second, technical, economic, and performance factors also alter the social acceptance of RET. For example, size, impact on the landscape, energy efficiency, CO2 emissions, investment costs, savings, and other factors remain pivotal. Third, and as already mentioned, individual predispositions and attitudes as well as contextual factors (e.g. distributional and procedural justice) remain decisive for social acceptance.

Extant literature also underscored the mediating role of individual-level variables and the inherent trade-offs in social acceptance. Perlaviciute and Steg (2014) highlighted the overarching effect of individual values in mediating the evaluation of energy technologies. In line with Devine-Wright et al. (2017), sociocultural and public factors mediate the evaluations of energy technologies, with information also playing an important role (Author, in press). Stadelmann-Steffen and Dermont (2018) proved that acceptance involves trade-offs between technical and sociopolitical factors (e.g. maximising production capacity versus reducing the impact on the landscape) that are (partially) driven by individual attitudes and predispositions. Therefore, it is key to learn about these trade-offs and anticipate how individuals will negotiate them to develop an RET with a technological configuration that maximises the likelihood of being widely accepted, and ultimately becoming a product for the market. In their article, Jayaraj, Klarin, and Ananthram (2024) also highlighted this multilevel perspective to ensure residential solar energy storage uptake.

The IPCC's report (Masson-Delmotte et al., 2018) differentiates mitigation and adaptation technologies. Mitigation technologies, such as energy storage solutions, aim to reduce fossil fuel consumption and greenhouse gas emissions to mitigate the effects of climate change. A growing body of research has concentrated on the social acceptance of energy storage solutions. In detail, this literature has scrutinised the perception of energy storage in the media (Fabiani, Fronzetti Colladon, Segneri, & Pisello, 2023); the legal, social, and cultural barriers in the residential sector (Simo-Solsona, Palumbo, Bosch, & Fernandez, 2021); and the intention to adopt battery storage at the household level (Agnew & Dargusch, 2017). Although the literature indicated a low awareness of energy storage technologies, it confirmed the potential of these technologies in terms of acceptability, with many stakeholders considering that energy storage will contribute to energy independence, efficiency, and climate change mitigation (Ambrosio-Albalà, Upham, & Bale, 2019; Jones, Gaede, Ganowski, & Rowlands, 2018). Recent literature also incorporated energy storage in the acceptance of an RET, measuring relative or cross-technology acceptance (Ladenburg, Kim, Zuch, & Soytas, 2024). However, this article considers that a missing piece in this literature remains STES.

2.3. Bridging the gap between technological development and social acceptance

Although the TAM and the TAF share strong similarities with the literature on social acceptance, it must be said that, in most cases, the technological development of an RET and research on social acceptance have remained two separate spheres. This is where a CTA comes into play.

The objective of a CTA is to embed social aspects in the context of technological developments to resolve the dichotomy between the benefits of a technology and its risks—that is, the technology dilemma (e.g. see Collingridge 1980, Schot and Rip 1996). For new technologies living in uncertain futures, the rationale underlying CTA has been to include more actors and, thus, more perspectives in technological development. One pivotal actor has been the society, specifically the (future) end-users of the new technology. Thus, CTA has become a promising approach that emphasises the idea of a society that shapes technology (Genus & Coles, 2006). It departs from the observation that choices are constantly being made during technological development and these choices related to the technology itself could be steered, to a certain extent, by the society—that is, (future) end-users.

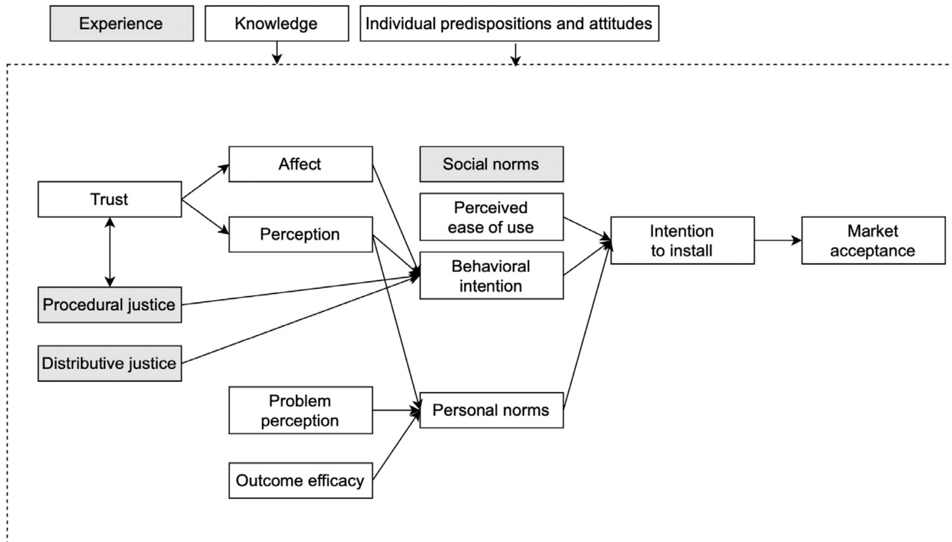

Fig. 1. Technology acceptance framework (TAF) in the early phase of technological development.
Note: Proposed TAF with the deleted factors in grey. These factors cannot be measured in the early phase of technological development.

By definition, technological development is driven by the actors involved and diffused in the society via different channels over time (Rogers, 1995). In the early development phase, their mapping of the technology takes place in the context of uncertainty and with a risk of failure. Garces, Daim, and Dabic (2023) confirmed that R&D decisions are not only complex because they involve many factors, but also take place in a context of high uncertainties. Information emerges gradually and different perspectives must be considered. Nevertheless, the decisions taken at the project's onset are decisive because the technology is still malleable (Versteeg et al., 2017). Technology loses this malleability during the development phase because of the expansion. This process of entanglement is inherent in technological development. It represents the consequences of irreversibilities arising from decisions taken by the enactors involved. In other words, these decisions shape the technology in a certain direction from where, in certain cases, there is no turning back (van Merkerk & van Lente, 2005). Further, Rip and te Kulve (2008) defined two categories of actors that play a role in technological development. First, enactors are the ones who develop the technology itself. They are developers, engineers, manufacturers, or investors. Second, selectors are the ones who eventually use the technology; this includes individual users, institutions, scientific actors, and legislators (Schot & Rip, 1996). In line with CTA, this study assumes that selectors must be involved as soon as possible in the development phase to provide input that can be integrated while the technology is still malleable.

Thus, the principal aim of CTA is to bridge the gap between technological development and sociopolitical acceptance of the technology. Including the society in an early phase, it broadens technological design, includes more reflexivity, and offers a comprehensive view of technological development (Doorn, Schuurbiers, van de Poel, & Gorman, 2013). Nevertheless, the main challenge for CTA is to involve technological selectors – that is, the end-users – rather than experts or organisations. Hence, the end-users might face an informational deficit that impedes them from evaluating their decision preferences regarding the technology. In their article, Assefa and Frostell (2007) conducted a questionnaire to encompass social acceptance in technology assessment. They concluded that respondents can hardly discuss future energy technology because of their low level of information and knowledge. The authors explain that respondents might voice an overall acceptance but have difficulty assessing acceptance of a specific future technology. Further to this, the so-called knowledge deficit model suggests that lacking knowledge regarding a policy, an issue, or a technology goes hand in hand with lower acceptance (Rhodes, Axsen, & Jaccard, 2014; Stoutenborough & Vedlitz, 2014).

In summary, this section highlighted a gap in the existing literature. Although it pinpointed numerous models and papers related to technology and social acceptance and explained how CTA calls for earlier involvement of society in technology development, it underscored the challenge to bridge the gap between technological development and social acceptance. No studies so far have focused on CTA and RETs.[3] However, the following challenge remains: How to assess behavioural intention to install a technology for (future) end-users with limited information regarding a technology that is in the development phase?

3. Conceptual framework

This study assumed that a more reflexive approach is suitable to shape the technology sufficiently early to avoid irreversibilities—that is, entrenchment. It built upon the TAF (Huijts et al., 2012) because this comprehensive model has been specifically designed for RET. It then fine-tuned this model to match a case of early involvement in the technological phase development of a new, unknown RET. Fig. 1 presents this TAF in the early phase of technological development.

To adapt the TAF to not only an early phase of development but also to findings on the social acceptance of RET, this article excluded four dimensions and included one. First, it replaced the intention to accept with the intention to install – that is, market acceptance – an RET. Although this article departs from the definition of social acceptance given by Wüstenhagen et al. (2007) it exclusively studies only one dimension—market acceptance. Considering that the sociopolitical acceptance of any RET is more or less given in general (for a review see Batel (2019), Segreto et al. (2023)), this article follows scholars' recommendations to focus on market and/or community acceptance, which remain the main barrier to the deployment of RET (Stadelmann-Steffen & Eder, 2020; Sütterlin & Siegrist, 2017). Further, the method

[3] One noteworthy exception is Versteeg et al. (2017), who explored the acceptance of battery technology for grid-connected energy storage using a CTA approach. They interviewed and surveyed relevant actors in the field of energy storage. The findings revealed a divide between the users and the developers, notably regarding the barriers to technological development and acceptance.

presented combines individual-level characteristics and technological features to evaluate market acceptance. It assumes that these factors most drive the intention to install an RET in one's own house.[4]

Second, this article considered that *social norms* can barely be assessed. Following the TPB, social norms capture the perception of how the social environment will endorse the technology (Ajzen, 1991; Ajzen & Fishbein, 1980). Considering that this technology has not yet reached the market, it is assumed that end-users can evaluate their preferences for the technology but cannot explore the evaluation of their social environment.

Third, the article refrained from including *experience* as a mediating variable. Although individuals can hold some knowledge of a technology that has not yet been marketed, they do not have any experience with this technology. Nevertheless, individuals can have experience or affinity with related energy technologies. Three individual-level characteristics were included in the TAF model to approximate such energy technology affinity – that is, *energy system with solar energy* and *energy system with heat pump* – that measures if individuals have such energy technology in their homes and *prosumerism* that measures if individuals have already invested in a RET. Although these measurements do not measure experience with STES, they approximate the affinity with an RET to provide an encompassing TAF model.

Fourth, this study selected market acceptance of STES at a single-family house level as a case to illustrate the proposed method. With a focus on market acceptance, the dimensions *procedural* and *distributive justice* are no longer part of the acceptance framework. Indeed, costs and benefits are the sole responsibility of the end-users and, subsequently, only the end-user is involved in the decision-making process.

Further, this article extended the TAF with individual-level attitudes and predispositions towards RET. Hence, *external variables* – for example, income, sex, or attitudes towards the environment – play a pivotal role for individuals assessing an energy technology, particularly when they are initially barely informed about it (Milani et al., 2024; Stadelmann-Steffen & Dermont, 2018; Venkatesh & Davis, 1996). These variables mediate the affect and perceptions, which then shape their behavioural intention to install the RET.

4. Materials and methods

The objective of this study is to illustrate how a conjoint experiment with a supervised ML model with OLS regression can predict the behavioural intention of (future) end-users in the early phase of technological development. To do so, it benefits from a novel online cross-section survey, with a conjoint experiment on the acceptance of STES in Switzerland at the single-family house level. Hence, a survey is ideal to assess the acceptance of a (future) technology. Not only does it involve lay individuals who are directly concerned with market acceptance – that is, (future) end-users – but also ensures a sufficient number of observations to fit a supervised ML model.

4.1. Survey design

The novel online cross-section survey was conducted in Switzerland between June 2023 and August 2023. It was a trilingual survey (German, French, and Italian). Participants were recruited via the polling agency LINK Marketing Services AG (YouGov Switzerland). To be precise, participants were recruited from the Federal Statistical Office (FSO) sample frame for household surveys and received a paper letter with an invitation hyperlink and a password to access the survey. This implies that participants had to opt in. The survey could be filled in on a computer or a smartphone but participants were strongly encouraged to use a computer (or a tablet) to ease comparison in the conjoint experiment.

The survey consisted of three parts and lasted approximately 25 min. The first part evaluated STES knowledge and attitudes related to the environment–energy debate. The second part included the conjoint experiment. The third part incorporated political-related and socio-demographic questions. To ensure representativeness, a quota sampling method stratified on cantons (70% German speaking-cantons, 25% French-speaking cantons, and 5% Italian-speaking cantons) was used. Ultimately, this study included $N = 1008$ participants for the conjoint experiment.[5] Further, 47.51% of the participants identified as female, and the average age is 49.18 years.

4.2. Case selection

For the purpose of this study, the technology that was selected had to fulfil two aspects. First, the market acceptance of the selected technology had to be uncertain. Second, the features of the technology had to still be malleable—that is, it had to be in an early phase of technological development. With this in mind, this article opted for market acceptance of STES as a case selection.

Looking at Switzerland, the Federal Statistical Office (FSO, 2023) indicates that the share of renewable energy in the energy mix accounts for approximately 28% in 2021. This is more than that in the EU (19%) but less than in front-runner countries such as Sweden (60%) or Finland (44%). The so-called new RET – that is, solar PVs, wind, biomass, and small hydropower – account for only 7.8% of the total electricity production. The literature has also indicated that the extended rights for public participation have been hindering the actual implementation of energy infrastructures at the local level, with the population combating siting decisions (e.g. Broughel & Wüstenhagen, 2021; Vuichard et al., 2022). Thus, the government and the parliament have been modifying or implementing ordinances or laws to boost RET development in Switzerland since 2022 (Zumofen, 2022). This confirms that Switzerland must find a way to bridge the gap between technological development and social acceptance to reduce the failure of RET implementation.

Seasonality is a pivotal feature in decarbonising the energy system not only in Switzerland but also worldwide (McKenna et al., 2019; Shah et al., 2018). Rather than being a renewable source of energy in itself, STES is a complementary energy infrastructure that transfers renewable energy production – for example, solar energy – over seasons. Indeed, a large part of the end-use energy fulfils either heating or cooling purposes, which display a strong seasonal character: in winter, people consume much more heat, and in summer people strive for more cooling. Renewable energy production displays a similar seasonal character. Therefore, STES can either store (surplus) heat in summer to use in winter or transfer cold from winter to summer for cooling purposes (for more details see Xu, Wang, & Li, 2014; Yang et al., 2021). This study supposes that STES is currently a missing piece in the energy transition, notably in Switzerland. While Switzerland exports surpluses in the summer, it has to import roughly the same amount of electricity in the winter months (FSO, 2023).

[4] Additional factors could be integrated to obtain a finer-grained evaluation of market acceptance. For example, policy-related factors such as landscape regulation or subsidies could be added to the conjoint experiment. Although such inclusion is possible in a conjoint experiment, including additional factors in the experiment is a trade-off between external and internal validity with the risk of overloading participants.

[5] The recruitment of participants consisted of three samples. First, a few participants belong to a panel sample because this survey is part of an overarching project. The panel participants already participated in the first survey wave in the autumn of 2022. Second, a few participants were extracted from an additional FSO household sample and were fresh participants—that is, did not participate in the first wave. Finally, a sample of stakeholders was also surveyed. Nevertheless, the stakeholder participants were not included in this study and, thus, do not belong to the dataset.

Further, most STES technologies are not mature yet and remain in the rather early phase of technological development (for a review, see Pourahmadiyan, Sadi, & Arabkoohsar, 2023. This study is timely to bring social science and energy engineers closer together to develop STES technologies with features that match (future) end-users expectations. In detail, this study focuses on five different STES technologies: water tank storage, ice storage, thermochemical storage, borehole storage, and latent heat storage. These STES technologies differ in terms of storage material—that is, energy density, technical parameters (e.g. size), economic parameters (e.g. savings), and performance parameters (e.g. CO2 emissions). The five STES technologies also belong to the three basic STES types: sensible heat storage, latent heat storage, and thermochemical heat storage (Xu et al., 2014; Yang et al., 2021).

4.3. Role of (additional) informative material

Recent literature on social acceptance (e.g. see Kadenic et al. 2024, Sovacool et al. 2022a) and the historical literature on CTA (e.g. see Doorn et al. 2013, Schot and Rip 1996) postulate that acceptance research and practice should apply a proactive rather than a reactive approach to examine social acceptance before the (energy) technology reaches the market to avoid barriers and failure. Nevertheless, with a technology in the early phase of technological development, a major challenge is the level of information available regarding the technology. This article takes for granted that most individuals have relatively low (or no) knowledge regarding the RET at stake given the relatively low awareness in the Swiss population. A challenge that comes up is to provide (future) end-users with sufficient information to form a behavioural intention regarding a technology that is barely known. Following De Best-Waldhober et al. (2009) recommendation, the innovative method presented in this article provides a substantive level of neutral information regarding the (energy) technology to circumvent the risk of non-attitudes. This information must be technically valid and unbiased in order not to influence perception.

In this article, survey participants were provided with two informative texts to contextualise the conjoint experiment and enable participants to form a behavioural intention. On the first page, an introduction text with stylised pictures summarised what STES is. In this text, STES was described and framed as an energy technology that can facilitate energy transition. For further details, see Fig. 7 in the Appendix. On the second page, more detailed information was provided to contextualise the conjoint experiment. The text introduced five assumptions on which the attribute and levels of the conjoint experiment were defined: the size of the residential area (i.e. how many apartments), the size of the apartments (in meter square), energy bill without an STES technology, connection with solar PVs and the power of these solar PVs, heating and cooling self-sufficiency without an STES technology, and the maximum lifetime of STES technology. To ease understanding and memorisation, the five assumptions were presented in the text and with a stylised picture. For further details, see Fig. 8 in Appendix.

It is worth noting that (1) by clicking on an information button survey, participants could refer back to the assumptions (text and stylised pictures) at any time during the conjoint experiment, and (2) the informative material has been developed in collaboration with a team of energy engineers with expertise in STES. This interdisciplinary process ensured technical validity while simplifying the content for lay participants (i.e. internal validity).

4.4. Operationalisation and measurements

To implement the TAF in the early phase of technological development, this study uses an online cross-section survey with a rating-based conjoint experiment to operationalise each variable. Fig. 2 depicts the TAF with the input and output variables, which fit the supervised ML model.

4.4.1. Input variables—individual-level characteristics

In line with literature in social science, this study assumes that individual-level variables directly or indirectly influence behavioural intention. It is expected that sociodemographic characteristics play a pivotal role. For example, Marzouk, Salheen, and Fischer (2024) have recently demonstrated that implementation preferences of solar energy systems in residential areas are mostly driven by age. It is then necessary to include these variables in the ML model to obtain an encompassing understanding of the logic underlying the market acceptance of an STES technology. To fit the ML model with individual-level variables, this study uses standard survey questions to measure *sociodemographic characteristics*, *attitudes*, *knowledge*, *trust*, *problem perception*, *outcome efficacy*, and *personal norms*. These questions were presented in the first (before the conjoint) and the last (after the conjoint) portions of the survey.

Sociodemographic characteristics This study included sociodemographic characteristics as input factors in the ML model: *sex* is a binary variable that takes the value 0 (male) and 1 (female); *age* is a continuous variable ranging from 16 to 95; *education* is an ordinal variable ranging from 1 (no diploma) to 12 (university diploma); *income* is an ordinal variable ranging from 1 (less than CHF 4,000 per month) to 6 (more than CHF 15,000 per month);*residential situation* is a binary variable with two categories (owner or tenant); *energy system with solar energy* is a binary variable that takes the value of 1 if the participant is living in a building using solar energy, and 0 otherwise; and *energy system with heat pump* is a binary variable that takes the value of 1 if the participant is living in a building using a heat pump, and 0 otherwise.

Attitudes Attitudes regarding energy, climate, and the environment were also included as input factors in the ML model: *energy importance* is an ordinal ranging from 1 (not important at all) to 5 (very important), *power failure concern* is an ordinal variable ranging from 1 (not concerned at all) to 5 (very much concerned), *energy price concern* is an ordinal variable ranging from 1 (not concerned at all) to 5 (very much concerned), and *energy independence concern* is an ordinal variable ranging from 1 (not concerned at all) to 5 (very much concerned). A variable to capture the *tradeoffs between renewable energy production and landscape conservation* was also included. The exact wording was 'The expansion of renewable energy production might conflict with landscape protection. Do you want a Switzerland in which landscape protection is more important than the expansion of renewable energy production or a Switzerland in which the expansion of renewable energy production is more important than landscape protection?' This variable is a continuous variable ranging from 0 (landscape conservation is a priority) to 10 (renewable energy production is a priority),

Knowledge This study measured *STES-related knowledge* with a self-reported question tapping into the level of knowledge regarding STES. This is a 6-point scale variable ranging from 0 (Never heard about STES) to 6 (Very high knowledge of STES). The exact wording was 'How familiar are you with seasonal heat storage?'. This question was asked before the conjoint experiment.

Trust To measure *trust*, this study used two different variables. First, it measured *trust in the energy provider* using a 10-point scale ranging from 0 (no trust at all) to 10 (absolute trust). Second, it measured *trust in the energy consultant* with a 10-point scale ranging from 0 (no trust at all) to 10 (absolute trust).

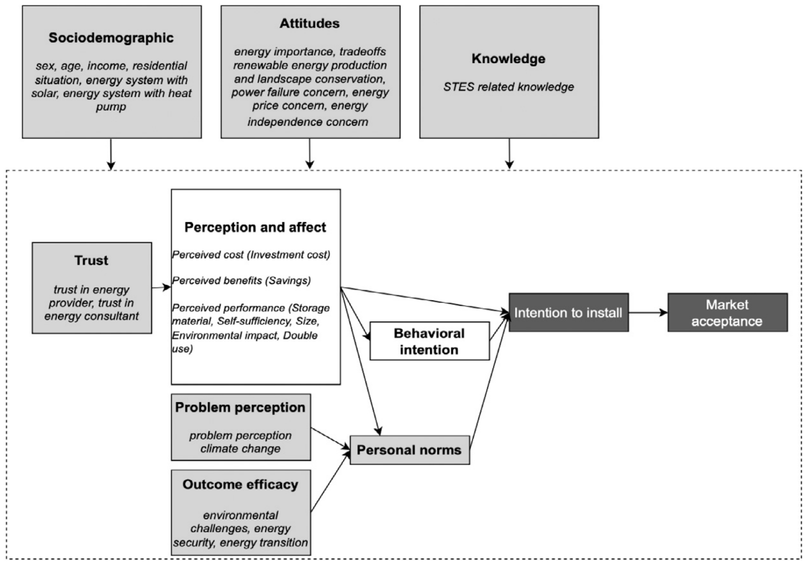

Fig. 2. Technology Acceptance Framework—operationalisation in a survey.
Note: Output in dark grey. Input variables at the individual-level (i.e. independent of technological features) in light grey. Input variables from the conjoint experiment (i.e. technological features) in white.

Problem perception To measure the *problem perception regarding climate change*, this study employed six questions, which were then aggregated into one index (Cronbach's alpha = 0.84) on a 5-point scale, which ranged from 1 (absolutely disagree that climate change is a problem) to 5 (absolutely agree that climate change is a problem). For example, the items asked participants to position themselves on statements like 'It is already too late to solve climate change'.

Outcome efficacy Before running the conjoint experiment, participants were tasked to determine how important could be STES to solve environmental and energy security challenges and to contribute to the energy transition. With three different variables the survey measured *outcome efficacy* on a five-point scale ranging from 1 (not important at all) to 5 (very important) to (1) solve environmental challenges, (2) solve energy security challenges, and (3) contribute to energy transition.

Personal norms In line with the TPB (Ajzen, 1991), this study hypothesises that *personal norms* relate to the moral obligation to install or refrain from installing RETs. Thus, the survey measures *personal norms* with a question on prosumerism. *Personal norms* is an ordinal variable ranging from 1 (I will probably never invest in renewable energy production) to 5 (I have already invested in renewable energy production).

4.4.2. Input variables—technological features

Scholars in social science have demonstrated that a conjoint experiment is optimal for assessing the social acceptance of RETs (e.g. Stadelmann-Steffen & Dermont, 2021; Vuichard et al., 2022). Hence, the strength of a conjoint experiment is to simultaneously estimate the causal effects of multiple attributes and levels (Hainmueller, Hopkins, & Yamamoto, 2014). With a more realistic format than a traditional factorial survey experiment, it reveals individuals' preferences for variants of RET alternatives and isolates pivotal factors in social acceptance. Moreover, a conjoint experiment reinforces external validity by presenting participants with many alternatives. It is also less prone to the social desirability bias, as it provides participants with multiple justifications for their choices (Wallander, 2009). In addition, Vuichard et al. (2022) confirmed that a conjoint experiment is ideal for assessing the acceptance of new technology with limited market information. The successive paired choices with multiple attributes ensured that participants could assess their behavioural intention to install a technology they barely knew about.

In this study, the purpose of the TAF is to focus on technological features that remain malleable, assuming that these could then be adapted in the reflexive process (represented in white in Fig. 2). It concentrates on how these malleable features influence the perception of the technology. Thus, the attributes and levels (i.e. technological features) have been defined in an iterative and interdisciplinary process with a team of energy engineers with strong expertise in STES. Indeed, it is wise to ensure the technical validity of the levels to provide realistic combinations. Although it is correct that a few of the technological features are interrelated and not independent, it is worth noting that only one restriction was included in the conjoint experiment – that is, the one for the attribute size. This methodological approach follows state-of-the-art guidelines on how to run a randomised conjoint experiment – that is, the third assumption of randomisation of the profiles (Hainmueller et al., 2014). Instead, ranges of realistic values for each attribute given the different STES technologies were determined by a team of energy engineers with expertise in STES. Thus, it is expected that each combination falls within these realistic ranges.[6]

Table 1 displays the seven attributes and the levels of the conjoint experiment. These attributes were integrated into the TAF to assess market acceptance:

Storage material STES technologies vary in terms of the storage material they use to store energy over seasons. *Storage material* not only relates to performance with the energy density that comes with the material but could also relate to perceived risk with certain materials being perceived as riskier than others (i.e. chemical solutions).

Perceived cost A cost-related attribute is included to evaluate the perception of cost.

[6] However, it is important to note that 'realistic' can refer to already developed STES technologies as well as to STES technology that the engineers considered to be realistic in the future. This openness is important to enabling conjoint results on STES technologies that remain in their early phase of development or that could be developed in the future.

Perceived benefits To balance the perceived cost, the attribute *savings* was added. This fuels the participants' perceived benefits of the STES technology. It is worth noting that the *savings* can be positive, non-existent, or negative on the energy bill.

Perceived performance Last but not least, the features of the technology influence its performance. Stadelmann-Steffen and Dermont (2018) proved that acceptance involves trade-offs with individuals maximising the performance of the technology while still weighing their personal preferences. With that in mind, the conjoint experiment included four technical features as attributes. First, *self-sufficiency* remains a key performance parameter of STES. It measures the extent to which installing an STES technology will increase self-sufficiency in heating (and cooling). Second, *size* is a also typical feature that involves trade-offs. On the one hand, a larger STES could provide higher self-sufficiency, and could also be financially beneficial with economies of scale. On the other hand, larger STES have a greater impact on the landscape. Moreover, certain types STES technology can be completely buried while others cannot. Literature demonstrated that aesthetic integration and (in)visibility matters for acceptance (see e.g., Zhou et al. 2024). The size of the STES was measured in cubic meters. In discussions with the energy engineers, restrictions were also defined to separate above- and below-ground technologies to avoid illogical combinations. Third, *environmental impact* was used to capture how many years are needed, with this STES technology, to have a net positive impact on the environment. Fourth, *double use* is another pivotal feature of STES. In other words, STES can be used for either heating or heating and cooling. A larger number of features (i.e. heating and cooling) are obviously advantageous but also come with additional costs and a different net positive impact on the environment.

Table 1
Attribute list, sentences, and levels used in the conjoint experiment.

Attributes	*Text in the survey*	Levels
Storage material	The storage is	filled with water (Energy density = 50 kWh/m3). filled with ice (Energy density = 80 kWh/m3). filled with edible salt (Energy density = 150 kWh/m3). filed with synthetic wax (Energy density = 110 kWh/m3) filled with a chemical solution (Energy density = 300 kWh/m3). composed of boreholes and buried tubes (Energy density = 12 kWh/m3).
Investment cost	The investment cost (including land price) is	CHF 10'000 CHF 20'000 CHF 40'000 CHF 80'000
Savings	The energy bill for district's residents	increases by CHF 100 per year stays the same decreases by CH 2000 per year decreases by CHF 400 per year decreases by CHF 800 per year
Heating self-sufficiency	The heating and cooling self-sufficiency increases up to	40% 60% 80% 100%
Size	The full size of the system corresponds to	5 m3 (above ground) 10 m3 (above ground) 10 m3 (below ground) 20 m3 (above ground) 50 m3 (above ground) 100 m3 (below ground) 1000 m3 (below ground)
Environmental impact	The net positive impact on the environment starts in	5 years 10 years 20 years 50 years
Double use	The system can be used	for heating but not for cooling for heating and cooling

Note: The levels were randomly assigned to each paired choice task.
Note: Restrictions for the attribute size were either an STES technology above ground (i.e. storage material is water, edible salt, synthetic wax, chemical solution) or an STES technology completely below ground (i.e. storage material is water, ice, or boreholes and buried tubes).

4.4.3. Output variable—behavioural intention to install

For the purpose of this study, the rating-based conjoint experiment was employed to fit the supervised ML model.[7] Each participant replied to six paired choices each of which they had to rate the hypothetical STES on a scale of 0 (Not at all convincing) to 10 (Very convincing). The exact wording of the rating-based question was *'Regardless of which STES you prefer, how convincing do you find each of these alternatives on a scale of 0 to 10?'*

The rating-based question becomes the output of the ML model. This output variable is a continuous variable that ranges from 0 to 10 (for an example of a paired choice, see Fig. 10 in the Appendix). To run the ML model, the database was reshaped to have 12 observations for each participant. Indeed, each participant rated 6 × 2 STES technologies, thus yielding a total of $N = 12{,}096$ experimental ratings.

4.4.4. A supervised machine learning model

Once the data were collected through the survey, and notably the rating-based conjoint experiment, it can be exploited to run a supervised ML model. In brief, a supervised ML model uses input variables (X) to predict an output variable (Y). The input variables fit the machine learning algorithm to map a function from the input to the output variable $Y = f(X)$. The goal of a supervised ML model is to obtain a function that is precise enough to accurately predict the output variable when presented with new input data.

A supervised ML model requires coded data to train the model and find the best-fitted function. In this study, the output variable is market acceptance—that is, behavioural intention to install the STES technology. It is a continuous variable ranging from 0 (not convincing) to 10 (very convincing). Then, it uses a regression as a statistical approach to map a function that best fits the relationship between the input (i.e. the predictor) and the output (i.e. the target) variables. In a second step, this best-fitting function can be exploited to make predictions. For the purpose of this study, a supervised ML regression model with ordinary least square (OLS) regression was presented to predict market acceptance. This linear model minimises the sum of the squares of the residuals—that is, the distance between the predicted values and the target values. In the end, the ML model minimises the error between the predicted values and the actual values of the target variable. To determine the model's accuracy, this article uses the root mean squared error (RMSE). It displays the root of the squared mean of the distance between the actual and the predicted values. RMSE is a popular metric to assess the accuracy of a supervised ML model by reporting the information in the same unit as the target variable.

[7] We refrained from using the choice-based experiment because the individual-level variables could not be integrated into the ML model. In the case of a choice-based conjoint experiment, participants are tasked to select one of the two alternatives (or none). Nevertheless, their individual-level characteristics are the same for the technology they select and the one they do not select. This implies that the influence of individual-level variables cancels out with the experiment. On the contrary, a participant rates the alternatives independently from each other.

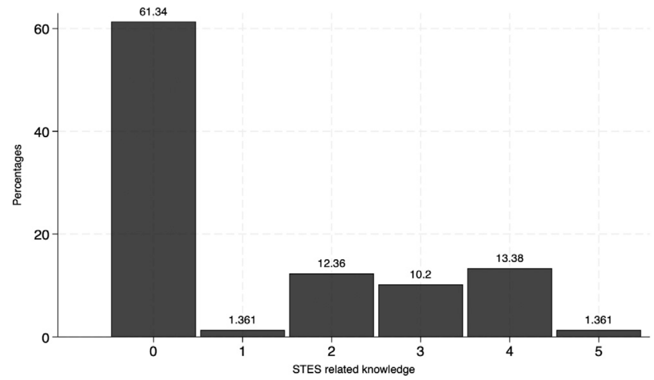

Fig. 3. STES-related knowledge.
Note: STES-related knowledge was measured prior to the conjoint experiment.

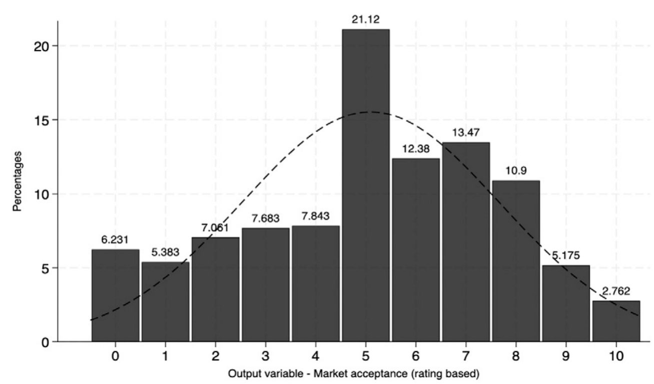

Fig. 4. Histogram of the output variable (Market acceptance).
Note: Rating-based question in the conjoint experiment.

5. Empirical results

To begin with, Fig. 3 displays STES-related knowledge of survey participants. As expected, most participants had a low level (or no) knowledge regarding the technology at hand. This not only confirms that most STES technologies are in the early phase of technological development but also pinpoints the pivotal role of additional informative material in the survey (see section 4.3). In detail, 61% of participants indicated that they had never heard about STES before this survey. On the other hand, only 15% asserted a rather high or high level of knowledge regarding STES. This low level of knowledge suits the purpose of this study and makes the conjoint experiment and the supervised ML model rather conservative, with a risk that causes many participants to be undecided regarding the profiles of STES technologies they are presented with.

Fig. 4 presents a histogram that evaluates the distribution of the output variable (i.e. behavioural intention to install). It confirms that participants gave a value of 5 – on a 0–10 scale – for a fifth of the profiles they were presented with. This peak can be interpreted as a rather high level of indecision. In line with the information deficit theory, it is postulated that this indecision is related to the low level of STES-related knowledge among the participants (see Fig. 3). Then, a Kurtosis measurement of 2.37 confirms that the output variable is close to a normal distribution, and a Skweness measurement of −0.28 indicates that the distribution is slightly left-skewed. These measurements evaluated the tailedness of the distribution relative to a normal distribution and the asymmetry of the distribution.

Before exploring how ML uses the input and output from a conjoint experiment to predict the market acceptance of a technology in the early phase of development, it is wise to have a look at the results of the conjoint experiments. Fig. 5 displays the marginal means of the seven attributes that were presented. The output variable is the rating-based question ranging from 0 (Not convincing at all) to 10 (Very convincing) at the single-family house level. First, the results highlighted a significant influence of the attribute *storage material*. STES technologies using boreholes and pipes as well as edible salt and water increased the probability that the technology is installed. Second, *investment cost* had a negative linear influence on behavioural intention to install – that is, the more expensive the technology is, the less likely it is to be installed. Third, *saving on the energy bill* had a significant positive influence on behavioural intention to install – that is, the more a participant saves on his or her energy bill, the more likely he or she is to install the STES technology. Fourth, with regard to *heating self-sufficiency*, only an increase up to 100% has a significant positive influence on intention to install. Fifth, the influence of *size* is complicated to disentangle. It seems that smaller STES infrastructures are more likely to be installed. Sixth, the *environmental impact* has a significant negative influence on intention to install if it takes 50 years to reach a net zero impact and a significant positive influence on intention to install if it takes (only) 10 years or less to reach a net zero impact. Last but not least, an STES technology that not only provides heating but also cooling features is more likely to be installed.

Verifying the robustness of the conjoint experiment, it is worth noting that most of the assumptions given by Hainmueller et al. (2014) were met. First, the levels were randomly allocated to participants. One noteworthy exception is the attribute *size*. For this attribute, a filter to differentiate between above- and below-ground technologies was designed. Second, the preferences of participants remained stable over the experiment (i.e. *no carryover effect*). Similarly, the ordering of the STES profiles within the paired choices did not influence the intention to install. To reach these two conclusions, separate conjoint models were run for the two first paired choices and the two last paired choices as well as for the rating tasks presented first and the rating tasks presented second. Fourth, together with the team of energy engineers, illogical combinations were excluded—that is, levels stuck to a realistic range based on the ground assumptions that were provided to participants as informative texts. Finally, it is necessary to note that the conjoint experiment did not respect the assumption of randomisation of the profiles. After careful consideration, it was decided to present attributes in the same order for the 6 × 2 profiles. The objective was to ease understanding and comparison across STES technologies for participants with initially low (or no) STES-related knowledge.[8]

Finally, this study presents a supervised ML model with OLS regression. This ML model uses both the individual-level variables and the technological features from the conjoint experiment as input variables to predict the output variable—that is, *behavioural intention to install* an STES technology at the single-family house level (for further details, see 2). To include categorical variables, they were transformed into multiple new binary variables using a one-hot encoding method. This transformation was needed for the attribute storage material in the conjoint experiment. In other words, the one-hot encoding method generated six binary variables that indicate whether the storage material – for example, chemical solution – was included in the STES profile presented to the participants.[9]

To predict *behavioural intention to install* an STES technology, this article trained the ML model with input variables–that is, the predictors. The ML model used 80% of the dataset to train the ML model and 20% of the dataset to verify the accuracy of the predictions. Fig. 6 displays the ML model with OLS regression. It compares the real output

[8] For further details regarding the assumptions, please contact the author.

[9] To factor in mutual exclusivity, it is worth mentioning that only one out of the five new binary variables can get the value of 1. The other binary variables will obtain a value of 0 because the same attribute cannot have multiple levels for the same observation in the conjoint experiment.

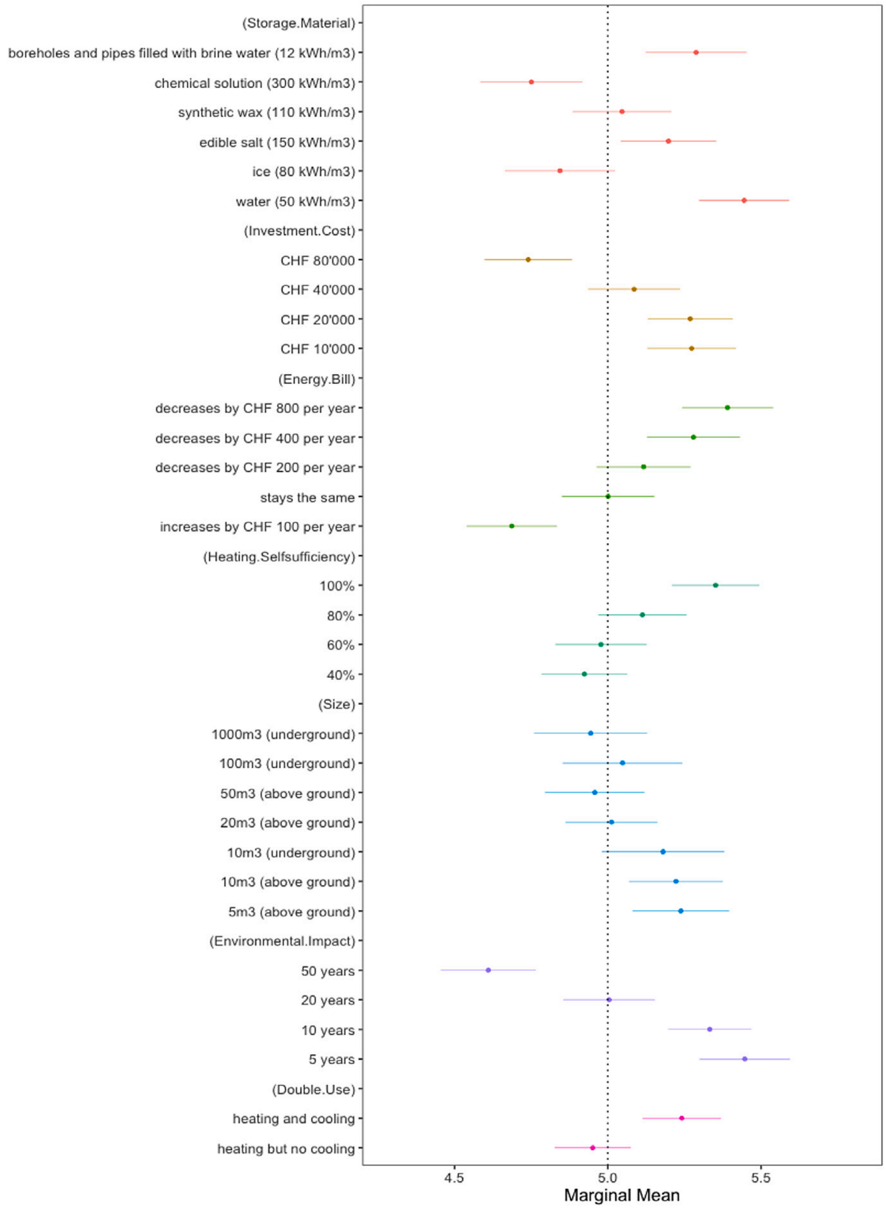

Fig. 5. Marginal means (MMs) from the conjoint experiment.
Note: Marginal means (MMs) represent the mean outcome across all appearances of a particular conjoint feature level, averaging across all other features. With rating-based questions ranging from 0 to 10 (output variable), MMs with values above five highlight technological features that increase the preference for the STES profile and values below five highlight technological features that decrease the preference for the STES profile.

with the predicted output. First, the ML model predicts outputs in a smaller range than real outputs. Although the real outputs vary from 0 to 10, (i.e. rating-based questions), the predicted outputs vary from only 2 to 9. It is assumed that the rather high indecision with a fifth of participants indicating 5 on the 0–10 scale (see Fig. 4) pulled the predictions towards the centre of the scale. Second, this article evaluated the accuracy with the RMSE. With the final ML model, a RMSE of 1.53 for the trained dataset and 1.55 for the test dataset were obtained. In other words, this implies that the predicted output is given within an error interval of 3.08. For example, if the model predicts an output of 7.5, the real output lies in a range of 5.95–9.05. In addition, the model computed a mean absolute error (MAE) of 1.93 (for the test dataset).

Once trained, this supervised ML model can be used to make predictions regarding the behavioural intention to install a STES technology. It is then possible to predefine mock individual-level variables and vary the technological features to predict the market acceptance of a future STES technology. Table 2 presents three different mock individual profiles with varying technological features for an STES technology. Then, using these profiles and technological features as new input variables, it is possible to predict the output variable – that is, behavioural intention to install – with an accuracy of RMSE = 1.53. With the mock examples in Table 2, the supervised ML model computed behavioural intentions to install of 4.40, 4.94, and 8.46 for the three profiles, respectively.

6. Discussion and conclusion

The chronic climate change threat and the more recent need to secure energy independence boosted research on the social acceptance of RETs. However, to the best of our knowledge, existing studies on social acceptance of the broad population have always taken place after the RET reached the market. At this stage, the energy technology is not

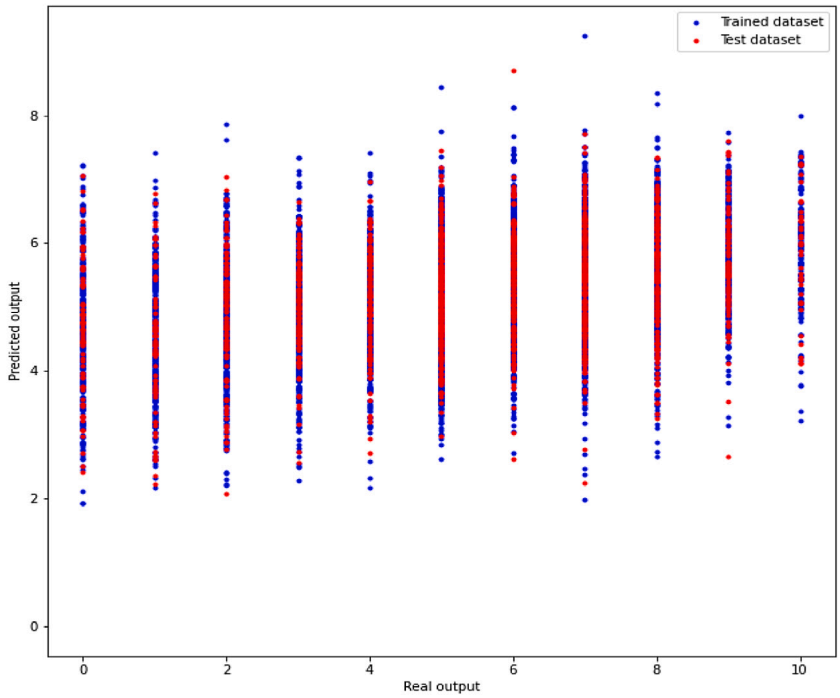

Fig. 6. Machine learning model with OLS regression to predict market acceptance. Note: The training dataset is 80% and the test dataset is 20% of the full dataset.

Table 2
Machine learning model predictions from three mock profiles.

Input - Individual-level	Profile 1	Profile 2	Profile 3
sex	women	women	men
age	35	50	42
education	University level	Federal Vocational Baccalaureate	University level
income	>CHF 15'000	CH 4'000 - CHF 6'000	CHF 10'000 - CHF 15'000
residential situation	owner	tenant	owner
energy system	solar panelsheat pump	nono	solar panelsno
energy importance	neither	neither	very important
tradeoffs REand landscape	8	4	9
power failure concern	not at all	not at all	very much
energy indep. concern	very much	not at all	very much
energy price concern	rather not	very	very much
STES-related knowledge	rather high	little	rather high
trust in energy provider	7	4	5
trust in energy consultant	3	3	5
problem perception textitclimate change	4	3	5
efficacy - environment	rather important	rather important	rather important
efficacy - security	very important	rather important	very important
efficacy - transition	very important	rather important	very important
personal norms	already	probably not	already
Input - Technological features			
storage material	synthetic wax	water	borehole with pipes
investment cost	CHF 80'000	CHF 20'000	CHF 20'000
savings (energy bill)	decreases by CHF 200	stays the same	decreases by CHF 800
heatingself-sufficiency	40%	80%	100%
size	5m3 (above ground)	50m3 (above ground)	100m3 (below ground)
environmental impact	5 years	5 years	10 years
double use	heating and cooling	heating	heating and cooling
Output - Behavioural intentionto install	**4.40**	**4.94**	**8.46**

malleable anymore. Although social acceptance scholars reach certain conclusions and make recommendations for the technology, it is too late because the development phase is over.

This was the starting point of this study. This article developed a method that combines a conjoint experiment with a supervised ML model with OLS regression to predict the market acceptance of STES. This method contributes to the literature on CTA, which aims at embedding social aspects, notably end-users, in technological development. It is a step further to bring technological development and social acceptance closer together. This method aligns with Kadenic et al. (2024) and Versteeg et al. (2017). This literature called for proactive (i.e. ex-ante) research and examination of practices on the social acceptance of (energy) technologies in the development phase. In other words, social acceptance must be determined prior to technology diffusion. Embedding social aspects earlier in the development phase has the potential to avoid irreversibilities, which could constrain social acceptance when the technology reaches the market.

This article illustrated this methodology using STES as an application. The ML model achieved a TAF for technology in the early phase of development. In brief, the ML model exploited as input both the individual-level variables extracted from the survey questions and the variation in technological features from the conjoint experiment to predict behavioural intention to install STES—that is, market acceptance for a technology. A major contribution of this article is to extend (Huijts et al., 2012) TAF to the case of technology in the early phase of development when social norms and awareness are minimal or lacking. This is in keeping with De Best-Waldhober et al. (2009), who recommended providing participants with substantial neutral information regarding an unfamiliar technology to prevent the risk of measuring non-attitudes or pseudo-opinions. To generate this information, this article opted for an interdisciplinary collaboration with a team of experts on the technology in question. This iterative process safeguards the technical validity and neutrality of the information while ensuring that the information is understandable for laypeople with no experience with the technology.

In brief, with a trained model of 80% of the dataset, the ML model predicted the output with an accuracy of RMSE = 1.55. In other words, the difference between the predicted and the real output lay within a range of 3.1 on a 10-point scale. Though the accuracy of the method remains questionable in this specific case, the strength of the article is to demonstrate that this innovative method works. Thus, the ML algorithm mapped a best-fitted function from the input to the output variables and was then able to predict new output from mock profiles with predetermined individual-level variables and technological features. Interestingly enough, the results indicated that many participants had a difficult time forming a behavioural intention. In other words, a fifth of the outputs indicated a value of 5 on the 10-point scale. On one hand, this is no surprise as participants had a low level (or no) of knowledge regarding STES, which is a technology in its development phase and is not a marketable product yet. On the other hand, this indecisiveness pulled the predicted value towards the centre of the scale. This might be a recurrent problem in the case of new technology. Thus, it should be addressed in further studies.

Finally, from a methodological perspective, this study contributes to two literature fields. First, it contributes to the CTA literature by designing a method that includes end-users in technological development. Considering practical implications, this method stands as a ready-to-use solution to embed social aspects early in the technological development phase (Doorn et al., 2013; Versteeg et al., 2017). Technological enactors can develop a survey with a conjoint experiment to predict technology acceptance in the early phase of technological development even when a technology is experimental. This speaks to recent research that explores expert opinion on the social acceptance of experimental technologies, such as negative emissions, geoengineering, or chemical solar energy storage (Kadenic et al., 2024; Sovacool et al., 2022a, 2022b). This innovative method can reduce the risk of market failure by guiding technological development—that is, avoiding irreversibilities that then become constraining factors in market acceptance. Second, it also contributes to the literature on conjoint experiments. Using conjoint data to run a supervised ML model is an innovative method that must be further explored. Therefore, this method extends recent research on social acceptance that regularly exploited the conjoint experiment method to study the multidimensional choice of the acceptance of an RET (e.g. see Stadelmann-Steffen and Dermont 2021, Vuichard et al. 2022).

This article also furthers (Sovacool, 2014) pioneering claim that social acceptance of technology is overlooked in the energy research agenda. It methodologically expands research on social acceptance to suggest a method to examine social acceptance in the technological development phase and reach out to the energy research agenda. To attain this goal, it relies on the recent social science literature that has concluded that acceptance is driven by three factors—that is, technological features and contextual and personal factors (for a review, see Milani et al. 2024). It confirms the importance of taking the multi-level perspective into account (Jayaraj et al., 2024) to predict social acceptance with higher accuracy. The conjoint experiment confirmed that (future) end-users favour a STES using either water or the ground as storage material, with a lower investment cost (below CHF 20,000) and with potential saving (higher than CHF 400 per year), thereby allowing higher heating self-sufficiency (100%) with a small impact on the environment and with heating and cooling features. This corresponds to the influence of technological features. But then, combining this dataset with the individual-level characteristics and running an ML model, this article confirms that personal factors also play a role in reaching an accuracy of RMSE = 1.55 to predict the market acceptance of any predetermined STES with varying technological features and personal factors.

Overall, this study is a step further in bringing technological development and social science closer. Employing an innovative method, it included (future) end-users earlier in the development phase. This method enables technology enactors to make development decisions that match (future) market acceptance of the (energy) technology. The next steps are to apply this method (1) to other emerging technologies and (2) to different ML methods and operationalisation. This article is a first application of an innovative method to exploit data obtained from a conjoint experiment. It is necessary to test this method on additional (energy) technologies that are not in the market yet to determine the extent to which the method could or should be implemented in the development phase of any technologies that might face reluctance in terms of acceptance once they are in the market. Further, applications could determine the extent to which including a method combining a conjoint experiment with an ML model in a CTA is relevant for technology enactors in practice and in the social acceptance literature in general. Practically, this method could anticipate and prevent market failure of future (energy) technologies.

In addition, future studies should fine-tune the ML model and the operationalisation of the output variable. Hence, this article applies a simple linear regression to survey data using a 0–10 rating-based question as an output. First, the model could test different output variables to measure market acceptance. The 0–10 rating-based questions could be re-operationalised to obtain a binary output or an ordinal output with different levels of acceptance. The rating-based question could also be combined with the classical choice-based questions displayed in a conjoint experiment. This re-operationalisation could help refine the output variable. Second, alternative ML models could be applied depending on the output variable used. For example, it could be insightful to run a logistic regression, a random forest algorithm, or a neural network to obtain a more accurate prediction model. However, this goes beyond the scope of this initial article, as this is only a first step to using a conjoint dataset with an ML model and not by computing traditional AMCEs or MMs. This implies that it is the first time that both individual-level characteristics and conjoint attributes and levels are examined together and not separately with subgroup analyses. Thus, the aim of this article was first to determine the relevance and applicability of the method before digging into the fine-tuned methods. This calls for further research on the subject.

CRediT authorship contribution statement

Guillaume Zumofen: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Appendix

See Figs. 7–10.

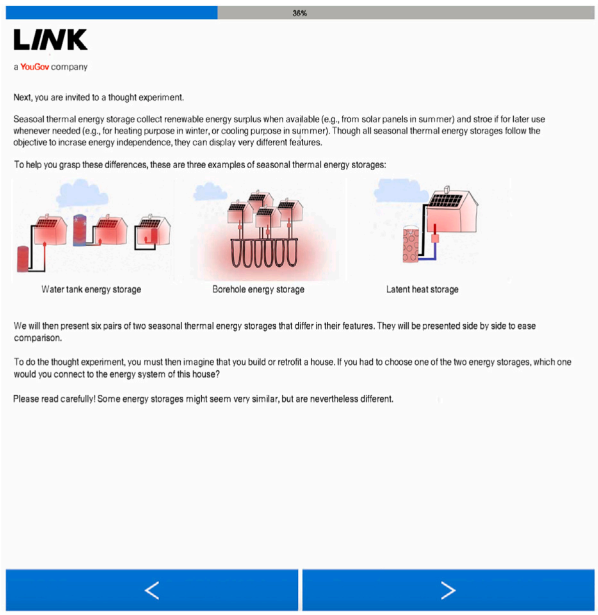

Fig. 7. Introduction - Conjoint experiment.
Note: English version of the informative text.

Fig. 8. Assumptions - Conjoint experiment. Note: English version of the assumptions.

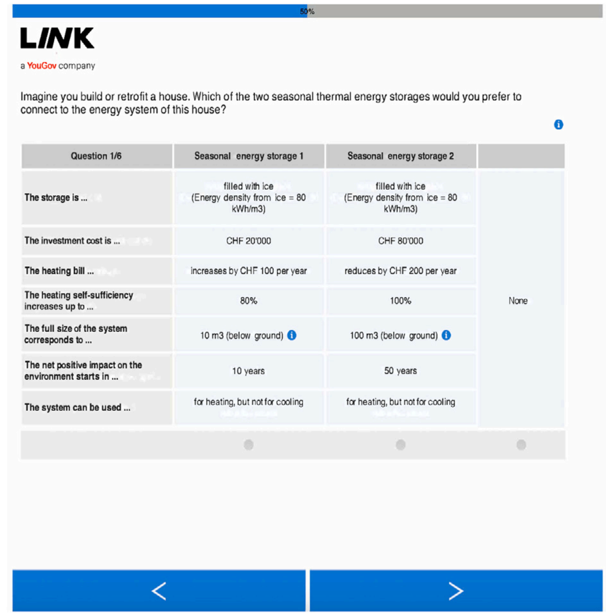

Fig. 9. An example of a paired choice.
Note: English version of the display of the conjoint experiment with the choice-based question and the 'None' option.

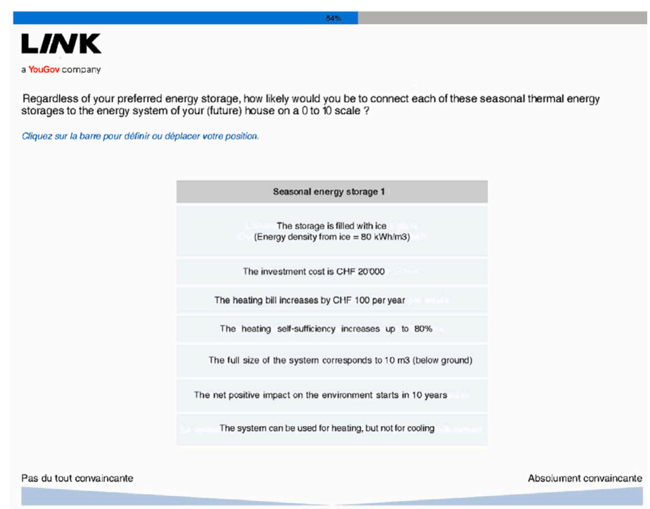

Fig. 10. An example of a rating-based question.
Note: English version of the display of the conjoint experiment with the rating-based question.

Data availability

Data will be made available on request.

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