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Research article

Extended reality-based choice experiment to assess the impact of offshore wind turbines in historic center: The case of Manfredonia

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A R T I C L E I N F O

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A B S T R A C T

This paper proposes a novel four-step methodology to achieve an extended-reality-based choice experiment in historic and touristic centers. The study exploits the case of Manfredonia (a seaside town in southern Italy) to apply the new approach and investigates public attitudes and preferences towards the installation of offshore wind turbines in the area. The novelty of the proposed work is twofold: i) for the first time, a structured methodological approach is defined for the development of a hybrid extended-reality-based choice experiment; ii) the perception of the visual impact of offshore wind turbines is assessed in a touristic and historic city in southern Italy exploiting the proposed approach. Our findings underscore the importance of continuously monitoring public perceptions to maintain and promote support for sustainable energy solutions, particularly in relation to the perception of wind energy's visual impact. In particular, 65% of respondents express their worries about wind power plants impact on the landscape. Moreover, the positive coefficient of the visual impact (0.011) suggests a positive utility of respondents from a higher off-shore turbines' density and a marginal willingness to accept a compensation of about 13€ for the visual impact and of about 33€ for the distance from the shore. In this context the use of extended reality technology in choice experiment scenarios significantly improves the results and enhances the understanding of the landscape impact of offshore wind farms.

1. Introduction

The visual perception of offshore wind turbines refers to how individuals perceive and evaluate the visual impact of these structures in the marine environment. Understanding how people perceive offshore wind turbines is crucial for effective planning, development, and acceptance of offshore wind energy projects. At the same time, it can help informing the decision-making, addressing concerns, and promoting effective communication strategies.

In the analysis of the visual impact of offshore farms in UK, Devine-Wright et al. (2014) argue finds that visual impact is of a significant concern for some individuals and this is particularly relevant during the planning and design stages to minimize negative perceptions and enhance public acceptance. Similarly, in the French case, Jobert et al. (2014) use a combination of surveys, interviews, and visual simulations to assess public attitudes towards offshore wind farms. The study reveals that the visual impact of wind turbines is a key factor influencing public acceptance, and suggests that the involvement of local communities in the planning process provides accurate visual representations thus helping to adequately address social concerns. Other studies explore the role of stakeholder engagement, community involvement, and communication strategies in shaping public acceptance (Walker et al., 2014; Zhang et al., 2017; Firestone et al., 2018; Bastiaans, 2023). On the one hand, an early engagement with local communities and stakeholders in the planning process provides opportunities for meaningful participation which can help addressing relevant concerns, building trust, and enhancing public acceptance. On the other hand, effective communication strategies provide the circulation of accurate information, by addressing misconceptions, and highlighting the benefits of offshore wind energy to positively influencing public perceptions and attitudes (Kim et al., 2020; Cronin et al., 2021; Park et al., 2022; Iwata et al., 2023; Gkeka-Serpetsidaki and Tsoutsos, 2023).

These studies highlight the importance of considering visual perception in the development of offshore wind energy projects. By understanding how individuals perceive and evaluate the visual impact of offshore wind turbines, developers and policymakers can take

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appropriate measures to mitigate negative perceptions and enhance public acceptance.

Other studies focus the attention on visual impact, aesthetics, and acceptance and emphasize the relevance of proximity to offshore facilities. In such cases, individuals living nearby hypothetical or existing offshore wind farms reveal stronger negative perceptions than other respondents, due to the altered coastal or marine landscape (Bishop and Miller, 2007; Ladenburg, 2009; Ladenburg and Möller, 2011; Maslov et al., 2017; Cronin et al., 2021; Gonzalez-Rodriguez et al., 2022)

The literature also examines the effectiveness of visual simulations or virtual reality in assessing public perceptions and preferences (Pitt and Nassauer, 1992; Scott, 2006; Diemer et al., 2015; Ribe et al., 2018).

Further topics of concern in determining public perceptions and attitudes towards offshore wind energy refer to the knowledge about renewable energy, environmental concerns, and socio-economic factors (Wiersma and Devine-Wright, 2014; Wever et al., 2015; Dalton et al., 2015; Caporale et al., 2020; Glasson et al., 2022). Many individuals perceive offshore wind energy as a positive step towards reducing greenhouse gas emissions (GHGs) and combating climate change. However, concerns about potential impacts on marine ecosystems, wildlife, and migratory patterns are also present (Bergström et al., 2014; Galparsoro et al., 2022; Pfeiffer et al., 2021). Nevertheless, public support for offshore wind energy is affected by the perceived economic benefits in favour to local communities, such as job creation, investment, and revenue generation (Adeyeye et al., 2020; Dinh and McKeogh, 2019).

Lucchi (2023) brings to the light the debate about the visual impact of offshore wind turbines in historic centers. The placement of offshore wind turbines near historic centers raises questions about the potential impact on the visual aesthetics and cultural heritage of these areas. The visual compatibility between offshore wind turbines and historic centers depends on various factors, including the distance, size, design, and color of the turbines. The visual impact can be influenced by the contrasting aspect between modern wind turbines and the historic architecture and landscape.

Historic centers often hold significant cultural and historical value. The introduction of offshore wind turbines in close proximity to these areas can potentially impact the sense of place, cultural identity, and heritage values associated with the historic center (Lamy et al 2020; Billing et al., 2022; Theodora and Piperis, 2022).

Furthermore, public perception and attitudes towards the visual impact of offshore wind turbines in historic centers can vary among different stakeholders, including residents, tourists, heritage organizations, and local authorities (Smythe et al., 2020; Trandafir et al., 2020; Bidwell, 2023). Balancing the interests and concerns of these stakeholders is crucial in decision-making processes. To address worries about visual impact, developers and planners may employ mitigation measures such as a careful turbine positioning, design modifications, or the use of alternative technologies to minimize the visual intrusion on historic centers. Engaging with local communities, heritage organizations, and other stakeholders in the planning and decision-making process can help ensuring that their concerns and perspectives are considered. Public engagement can also facilitate the development of solutions that balance renewable energy goals with the preservation of historic centers.

It is important to note that the specific visual impact of offshore wind turbines in historic centers can vary depending on the context, local regulations, and the specific characteristics of the area. Considering the complexity of the topic, the use of choice experiments (CEs) in studying offshore wind farm perceptions provides valuable insights into how individuals weigh different attributes and make trade-offs when evaluating these projects. CEs help informing decision-making processes, stakeholder engagement strategies, and the development of offshore wind farm projects that align with public preferences.

CEs have been widely used in the field of environmental and resource economics to understand public preferences (Adamowicz, et al., 1994; Hanley et al., 1998; Birol et al., 2006; Carson, et al. 2014; Chen et al., 2017; Tietenberg and Lewis, 2018) as well as to investigate perceptions related to wind energy (Börger et al., 2014; Caporale and De Lucia, 2015; Brennan and Van Rensburg, 2016; Peri et al., 2020; Ladenburg et al., 2020). The CE approach involves presenting respondents with a series of hypothetical scenarios or choice sets, each consisting of multiple options with varying levels of attributes. Respondents are then asked to choose their preferred option from each set or indicate their level of preference.

By analysing the choices made by respondents, researchers can estimate the relative importance of different attributes and assess the trade-offs individuals are willing to make. This information enables policymakers, developers, and stakeholders to grasp public preferences and tailor offshore wind farm projects accordingly, aligning them more effectively with the community's perception.

CEs offer numerous advantages when investigating perception as discussed below.

i) *Identifying and Quantifying Attribute Importance.* CEs allow for the identification and quantification of the relative significance of various attributes influencing perception. For instance, attributes like visual impact, distance from the shore, or economic benefits can be integrated into choice scenarios concerning offshore wind turbines. This aids in comprehending how these attributes sway perception;
ii) *Exploring Attribute Trade-offs.* Through systematic manipulation of attribute levels, researchers can gauge the trade-offs that individuals are willing to make between different attributes. This approach yields insights into the hierarchical importance of distinct attributes in shaping perception.
iii) *Evaluating Scenarios and Policy Options.* CEs enable the assessment of diverse scenarios or policy alternatives. By comparing individual preferences and perceptions across various scenarios, these experiments elucidate how alterations in attributes or conditions impact perception.
iv) *Leveraging Advanced Statistical Models.* Advanced statistical models, such as random utility models (RUMs), can be harnessed to analyze data and estimate preference parameters. These models account for pinpointing significant factors that influence perception and quantifying their effects accurately.

Furthermore, CEs can be used to evaluate different policy or management scenarios related to offshore wind farms. By comparing preferences and perceptions across different scenarios, researchers can assess the potential impacts of policy changes or alternative development options.

1.1. Proposal of the study

This paper proposes a novel methodology for an extended reality-based CE to assess the impact of offshore wind turbines in landscapes surrounding touristic and historic centers.

The study pursues three primary objectives.

1. To accurately define and describe the four essential steps of the novel approach: i) Defining the Choice Experiment (CE); ii) Designing the virtual environment through onsite survey and virtual environment design; iii) Implementing the VR-supported survey; iv) Launching the survey/experiment and conducting data analytics.
2. To provide a practical application of this novel approach by investigating public attitudes and preferences towards the installation of offshore wind turbines in the Manfredonia area, which is characterized by a unique and valuable cultural heritage.
3. To contribute to the analysis of existing trade-offs among variables affecting an offshore wind farm and to assess the environmental costs associated with the social damage to the local community.

The experiment employs an extended reality approach, enabling participants to experience a realistic representation of the turbines' visual impact on the surrounding landscape. By using this innovative methodology, the study aims to provide valuable insights into the public perception of renewable energy infrastructure and its potential impact on historic sites. The results of the study are expected to contribute to the development of effective policies and strategies for sustainable energy development in historic cities and cultural landscapes.

2. Theoretical background

2.1. Unified theory of acceptance and use of technology

The present work is a mixed approach of adoption of new technologies, such as off-shore energy that contributes to green and energy transition of a specific area of historical interest, and the use of VR technologies to help advancing the adoption of the off-shore in the considered area. To this end, the theoretical insight of this investigation is based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extension (UTAUT2).

Since the seminal paper by Venkatesh et al. (2003), the UTAUT approach has seen a significant increase in the international debate. It has emerged as a theory that combines several well-known theories, including the Theory of Planned Behaviour (TPB), Theory of Reasoned Action (TRA), Innovation Diffusion Theory (IDT), Social Cognitive Theory (SCT), Technology Acceptance Model (TAM), and the Motivational Model (MM).

The TPB, TRA, SCT, and IDT theories are examples of the socio-psychological perspective in individual behavior research. In contrast, the TAM, along with its variations like the C-TAM-TPB model, and the MM models, belong to the cognitive response perspective when analysing technology acceptance (Davis, 1986, 1989). These perspectives propose that understanding user motivations can help delve into technology adoption and usage behaviors. TPB and TRA analyze human behavior from a psychological viewpoint, focusing on variables like perceived behavioral attitude, control, and subjective norms (Manstead, 2001; Ajzen, 2011; Cooke et al., 2016). These theories offer universal insights into individual attitudes, making them applicable across various research contexts. They provide a theoretical framework for understanding human behavior. On the other hand, IDT concentrates on innovation-specific factors that influence users' behavior and their decisions regarding innovation adoption (Dosi, 1982; Rogers, 2003; Tortorella et al., 2021). Furthermore, these models offer distinct viewpoints, which are shaped by the variables they incorporate. These variables encompass motivational factors (Anwar, 2020; Coneybeare, 2020; MacEachern et al., 2020), subjective norms (Moon, 2020), technology performance-related attitudes (Zeng et al., 2020; Schwabe et al., 2021; Arora et al., 2022), social influences (Md Nordin et al., 2021; Lyu et al., 2023), experience and enabling conditions (Owen et al., 2002; Yang and Li, 2019). SCT operates under the premise that cognitive, behavioral, and environmental factors, such as outcome expectations in terms of performance and personal outcomes, anxiety, affect, and self-efficacy collectively exert an interactive influence on an individual's behavior (Andersen and Chen, 2002; Schunk, 2012). Choosing one of the aforementioned models limits research findings to specific situations and circumstances. Hence, there is a need for a unified approach that can incorporate variables from various perspectives and disciplines, thus expanding the theory's applicability to diverse contexts.

The current study employs an integrated approach to investigate innovation and the acceptance and adoption of technology delineated by the UTUAT (Venkatesh et al., 2003) and UTUAT2 (Venkatesh et al., 2012) theoretical insights. Notably, the UTAUT2, an extended version of the previous UTAUT, exhibits greater predictive capability and, given its enhanced suitability for social acceptance contexts, offers a more empirically suitable framework for the acceptance of sustainable technologies.

The aim of UTAUT2 is to provide a comprehensive framework for investigating technology acceptance. Therefore it offers greater accuracy in elucidating user behavior through the incorporation of new elements and constructs, addressing the attitudinal and behavioral factors influencing technology use in non-organizational settings (Venkatesh et al., 2012). UTAUT2 introduces three novel constructs that modify certain relationships, such as the elimination of voluntariness, from the original model to tailor it to the context of consumer technology use. This approach provides a fresh, theoretically substantiated mechanism for forecasting technology acceptance. The three supplementary constructs include hedonic motivation, cost or perceived value, and habit. These are controlled by age, gender, and experience of the user.

Venkatesh et al. (2012) defines hedonic motivation "as the fun or pleasure derived from using technology, and it has been shown to play an important role in determining technology acceptance and use". In terms of cost or perceived value, using consumer technology entails a heightened sense of responsibility, given the direct expenses associated with its usage. The more affordable the costs, the more extensively technology is used. Since both approaches (i.e. UTAUT and UTAUT2) rely on subjective metrics, the cost aspect is expressed through price value.

Again, Venkatesh et al. (2012) define price value as "consumers' trade-off between the perceived benefits of the applications and the monetary cost for using them". Therefore, a positive correlation between the perceived benefit (or value) and intention to use suggests that the user views the benefits of technology as greater and more significant than the monetary costs involved.

Finally, Venkatesh et al. (2012) consider the third construct (i.e. habit), as "the extent to which people tend to perform behaviours automatically". The habit construct considers technology use as an instinctive and subconscious action. Habit is posited to exert both a direct and indirect influence on actual usage through behavioral intention. Nevertheless, the impact of these pathways hinges on the extent to which individuals trust their routine behavior when adopting or using technology.

The primary constraints of the UTUAT/UTUAT2 theoretical underpinnings, expressed as their inability to elucidate behavioral intention across diverse contexts and the necessity for employing alternative metrics to validate them, are at the core of the present work which extends the above drawbacks in the context of off-shore developments nearby a historical area with the use of VR technologies and CEs.

2.2. The support of extended reality-based choice experiment

In this context, novel technologies based on extended reality can enhance decision-making and, other than being increasingly important across a variety of research and application fields, contribute to a practical application of the UTAUT2 framework. ER tools can be classified in three main categories according to the recent literature (Cárdenas-Robledo et al., 2022; Kovacova et al., 2022; Alizadehsalehi et al., 2020): i) Virtual Reality (VR) that creates a fully immersive digital environment; ii) Augmented Reality (AR) able to overlays digital information onto the physical environment; iii) Mixed Reality (MR) that blends digital and physical environments, allowing for interactive experiences.

Extended reality can be a valuable tool for supporting decision-making methods. The potential of extended reality to enhance decision support in the built environment is well-demonstrated (Wang et al., 2013; Zhu and Li, 2021). Furthermore, the literature demonstrates that certain spatial extended reality tools can be helpful at the territorial scale when applied to urban design, geographic information systems, and large construction management (Feng et al., 2020). There are few effective attempts to use extended reality in support of multi-criteria decision-making processes in related literature. Sangiorgio et al. (2021) provide a first attempt to develop a multi-criteria decision-making method entirely developed within an extended reality environment. The research demonstrates the effectiveness of the novel tool and, in particular, shows the importance of displaying useful information in a virtual environment during the decision process (Sangiorgio et al., 2022).

Furthermore, VR shows promising evidence in assessing public perception and attitudes in various domains, including the evaluation of visual impacts and acceptance of different projects to promote climate change awareness VR provides a highly immersive and interactive experience, allowing participants to engage with realistic virtual environments (Xi et al., 2022). This immersive nature enhances the authenticity of the experience and elicits more genuine responses from participants (Fauville, et al., 2020; Nelson et al., 2020).

Moreover, VR accurately simulates visual representations of proposed projects, such as offshore wind farms or urban developments. This enables participants to assess the visual impact and make more informed judgments compared to traditional methods like static images or descriptions.

Since VR provides a better understanding of the spatial context and scale of a project, participants can explore the virtual environment from different perspectives, thus helping them to evaluate the potential impact on the surrounding landscape or community. Besides, form the point of view of behavioral observations, VR allows researchers to observe participants' behaviors and interactions within the virtual environment and this provides valuable insights into decision-making processes, preferences, and reactions that may not be easily captured through self-report measures alone (Huang, et al., 2020; Scurati et al. 2021). In contrast, while VR technology is nowadays more accessible, it still requires specialized equipment. Nonetheless, advancements in consumer-grade VR devices make it more affordable and easier to implement this new technology in research studies.

Regarding the support of CEs with extended reality, there are some examples in the recent literature. The studies are mainly focused on consumer decision-making (Neill and Lahne, 2022, Xi et al., 2022). In particular, Xi et al. (2022) demonstrates that AR does not affect the effectiveness of the results. Such a technique is very effective in assessing the impact of changes in the landscape in the surrounding area of urban and historic centers (specifically if characterized by tourist importance). AR and VR allow the user to visualize in an immersive environment (or improve the physical environment) for the hypothetical changes occurring in landscapes or buildings after the implementation of specific interventions (e.g. installation of solar panels or wind turbines). Among the very few experiments in this field, Bateman et al. (2009) supports a CE analysis to value land use changes by using VR to assess the changes in the studied territory from a bird's-eye view.

VR is an emerging technology that has the potential to revolutionize the way CEs are conducted. By creating immersive, interactive environments, VR provides participants with a more realistic and engaging experience, which may lead to more accurate and reliable outcomes.

One of the earliest studies exploring the use of VR in CEs is the work by Chorus et al. (2010). In this study, participants are introduced with a series of hypothetical scenarios involving different transportation modes and are asked to choose their preferred option. The scenarios are presented either in a traditional survey format or in a VR environment. The results show that participants in the VR group are more likely to choose the option that is most consistent with their stated preferences.

Several other studies explore the use of VR in CEs, including applications in healthcare, marketing, and environmental economics. For example, a recent study by Wang et al. (2021) uses VR to simulate different types of urban green spaces. The outcomes reveal that participants are more likely to choose options that provide them with a greater sense of tranquility and relaxation, compared to traditional CE approaches. Another study by Kühn et al. (2019) use VR to investigate the impact of product design on consumer preferences. Participants are presented with a series of product designs in a VR environment and are asked to rate their preferences for each design. The results show that participants in the VR group are more likely to choose designs providing more aesthetically pleasing and with a higher perceived value than the control group.

2.3. The boundaries of prior scholarly discourse

Overall, the use of VR in CEs is still in its early stages, but the potential benefits are significant. By providing a more realistic and engaging experience, VR may help to improve the accuracy and reliability of data collected through CEs, leading to better-informed policy decisions and more effective territorial marketing strategies. On the other hand, exhaustive and structured methodologies to support choice experiments with extended reality to assess the impact of actions taken on the territory affecting landscape (such as offshore wind turbines) are still missing in related literature.

In spite of the aforementioned recent studies, there has been a pronounced focus on quantifying the reduction in overall well-being linked to the visual effects of wind turbines. Nonetheless, a considerable portion of these investigations has used inadequate or absent visual representations to depict the envisaged visual impacts. Consequently, these studies heavily lean on the cognitive capacities of participants to visualize wind turbines of diverse scales and proximities. Specifically, Hevia-Koch and Ladenburg (2019) show a review and discussion of visualization approaches and concludes that the relevance and quality of any study examining the economic significance of visual impacts are closely tied to the scientific rigor employed by researchers in creating the scenario description and associated visualizations. The way visualizations are presented, the scaling of visual attributes, and the attributes represented in the visualizations of wind turbine scenarios can significantly influence respondents' perception of the quality of the good being evaluated. Therefore, conducting a study that includes a high number of visual attributes without ensuring the necessary quality of the scenario description introduces uncertainty regarding the basis on which respondents evaluate the visual images. This uncertainty can weaken the conclusions drawn from the study and provide less reliable grounds for application in policy decisions and economic analyses.

According to Hevia-Koch and Ladenburg (2019), the discourse centers on the utilization of visualizations in stated preference (SP) studies, highlighting the prevalent tendency of excluding visual representations. Consequently, there arises a need to enhance the caliber of scenario descriptions to accurately assess the aesthetic effects of wind turbines. The discussion underscores the importance of raising the bar in designing visual representations to enhance the accuracy and reliability of data collected through SP studies.

Given the above, the main objective of the present study is to address the existing gap in stated preference (SP) studies by integrating appropriate visualization tools to assess the visual impacts of wind turbines. By incorporating high-quality visual representations, the study aims to enhance the accuracy and reliability of data collected, allowing for a more comprehensive understanding of public perceptions and preferences towards wind energy projects.

3. Study area

The case study concerns the historic center of Manfredonia, located by the sea in the north of Puglia. In the following, a brief description of the city and its historical, artistic, and architectural assets is provided to explain the context in which the investigation of the offshore wind farm impact takes place.

The historic centre of Manfredonia is a charming medieval town located on the eastern coast of Italy, in the Puglia region. The town was founded in the 13th century by King Manfred of Sicily, and it is known for its rich history, picturesque alleys, and ancient architecture. The historic centre of Manfredonia is home to numerous landmarks, such as the Swabian Angevin Castle (a gothic castle built by the Angevins in the 13th century) and the Cathedral of San Lorenzo Maiorano. The historic centre of Manfredonia is a popular tourist destination, offering visitors a glimpse into Italy's fascinating past. The architecture is characterized by traditional white stone houses typical of the Apulian architecture. The wealth of artistic treasures extends beyond the historic center, such as the Archeological Park of Siponto including an innovative installation by a young artist from Lombardy, Edoardo Tresoldi made out of metal mesh (its forms evoke the early-Christian basilica's final building phase).

In addition, the selection of Manfredonia as a case study is notable due to its fusion of historical elements and its recognition as a beach tourism destination, owing to its diverse range of beaches. Indeed, the coastal stretch that Manfredonia proudly presents is adorned with a multitude of crafted shoreline establishments, it as an exemplary tourist destination that appeals to both enthusiasts of beach-related activities and individuals seeking sun-soaked leisure. For all the above reasons, the site of Manfredonia supports the case of a survey (see section 3.3) carried out at national level. Fig. 1 shows the aerial view of Manfredonia retrieved by Google Earth.

4. Methodology

This section proposes a novel procedure based on the synergistic combination of CEs and extended reality. In addition, proper approaches and employed software are also presented.

Fig. 2 shows an overview of the proposed methodological approach.

The **first step** exploits the classical theory of the CEs. In this phase, the questionnaire is defined by identifying attributes, levels and hypothetical scenarios.

The **second step** consists of the design and development of hypothetical scenarios in a virtual environment. This step exploits various software, techniques and approaches to allow the user to visualize, in an immersive environment, the presence of offshore wind turbines superimposed on the real context, through the use of specific photomontages.

The **third step** joints the questionnaire of the CEs with the hypothetical scenarios developed in the virtual environment through specific

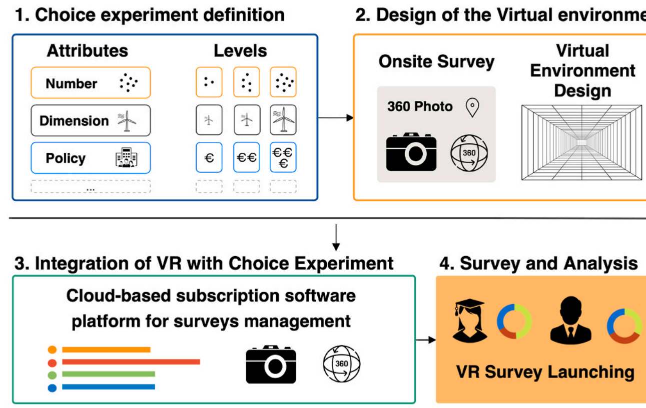

Fig. 2. The four step of the proposed methodology.

cloud-based software.

The **fourth step** lunches the survey and analyses the relevant results. Beyond the obtained sample, this last methodological step defines the statistical approaches to analyze the data collected.

The next subsections exhaustively describe the above defined four steps.

4.1. Step1: choice experiment definition

CE methodology is an SP technique used to elicit individuals' preferences and assess their decision-making processes. The application of the CE technique involves incorporating the characteristics of the theory of value (Lancaster, 1966) along with random utility theory (Thurstone, 1927; Manski, 1977). As a result, it shares close connections with the random utility approach to modelling recreational demand using revealed preference data (Bockstael et al., 1991). Participants are

Fig. 1. Aerial view of Manfredonia from Google Earth.

presented with various bundles of (environmental) goods and are asked to select their preferred option based on the attributes or characteristics of these goods, including price. To illustrate, let us consider a scenario where a respondent has to choose an offshore wind farm project. We assume that utility depends on choices made from some set C of offshore wind farm alternative. The representative individual is assumed to have a utility function as follows:

$$U_{in} = U\left(Z_{i,n}, S_n\right) \tag{1}$$

where, for any individual n, a given level of utility is associated with an offshore wind farm alternative i. Alternative i is chosen over some other option j iff $U_i > U_j$. Utility derived from any option is assumed to depend on the attributes of the offshore wind farm, Z, of that option (e.g., the visual impact of the surrounding landscape). The interpretation of these attributes can vary among different agents, and their utility can also be influenced by the socioeconomic characteristics denoted as S.

The utility function can be split into a deterministic and observable part (V), and ε, the error component, which is random and unobservable. Therefore, Equation (1) can be re-written as:

$$U_{in} = V\left(Z_{i,n}, S_n\right) + \varepsilon\left(Z_{i,n}, S_n\right) \tag{2}$$

and the probability that individual n will choose option i over other options j is given by:

$$Prob(i \mid C) = Prob\left\{V\_(i,n) + \varepsilon\_(i,n) \ > V\_(j,n) + \varepsilon\_(j,n), all\, j \in C\right\} \tag{3}$$

where C is the complete choice set.

To estimate Equation (3), certain assumptions need to be made regarding the distributions of the error terms. The commonly employed assumption is that the errors follow independent and identically distributed (iid) Gumbel distribution (as proposed by McFadden in 1974). Under this assumption, the probability of choosing i can be expressed as:

$$Prob(i) = \frac{exp^{\mu V_i}}{\sum_{j \in C} exp^{\mu V_j}} \tag{4}$$

Here, μ represents a scale parameter that is commonly assumed to be equal to 1, implying a constant error variance. As $\mu \to \infty$, the model becomes deterministic. Equation (4) is typically estimated using a multinomial logit model (MNL), which assumes that choices adhere to the Independence from Irrelevant Alternatives (IIA) property (McFadden, 1974; Greene, 1997; Maddala, 1999). This property states that:

> " for any individual, the ratio of choice probabilities of any two alternatives is entirely unaffected by the systematic utilities of any other alternatives" ((Ben-Akiva and Lerman, 1985: 108).

The IIA property can be tested in CE datasets, and if violations are detected, the standard RUM may no longer be applicable. The definition of the CE is of basic importance since participants are asked to choose their preferred option among the presented alternatives. By analysing the choices made by participants, it is possible to estimate the trade-offs of attributes and how they affect decision-making. CEs typically encompass multiple phases, as outlined by Hensher et al. (2005), which we are categorizing as sub-steps within the proposed methodology:

The **first sub-step** in a CE involves the identification of attributes that are relevant to the research question. These attributes should capture the key factors that influence decision-making and represent the characteristics or features of the options being evaluated. For example, in the context of offshore wind energy perception and according to the literature, attributes can include visual impact, distance from shore, noise levels, economic benefits, and environmental impacts.

As **second sub-step**, each attribute is defined by different levels or options. These levels represent the range of values or conditions that the attribute can take. For instance, the visual impact attribute may have levels such as "no visible impact," "moderate visual impact," or "significant visual impact."

The experimental design represents the **third sub-step**. A carefully designed experimental design is crucial for a CE. It involves creating choice sets, which are hypothetical scenarios that present respondents with multiple options, each defined by specific attribute levels. The design ensures that the attribute levels are systematically varied across the choice sets to capture respondents' preferences accurately. There are several experimental design techniques commonly used in CEs. To achieve efficiency in representing attribute space while simultaneously minimizing the number of choice sets, the current study employs D-Optimal DesignThe D-Optimal Design aims to maximize the precision of parameter estimation by selecting the choice sets that provide the most information retrieved from respondents' preferences. These designs consider the specific statistical model used for analysis and optimize the design based on criteria such as the determinant of the information matrix.

The fourth sub-step is Choice Task Presentation. Here the respondents are presented with the choice sets and asked to make a choice or rank their preferences among the options. The choices made by respondents provide data on their preferences and the trade-offs they are willing to make between different attribute levels.

Finally, the last sub-step relates to Data Collection and Statistical Analysis. The sample of respondents should be representative of the target population of interest. For this reason, a panel of certificated respondents are purchased by Qualtrics for the present study (Weber, 2021; Trandafir et al., 2020). The collected data represent the choices made by respondents for each choice set. In these phase, advanced statistical models, including RUMs (such as multinomial logit or mixed logit models), are used to analyze the CE data. The interpretation of the results of the statistical analysis allow to understand the relative importance of different attributes and the individual trade-offs providing valuable insights into how they weigh the various aspects of a wind energy project. These results can inform decision-making, policy development, or further research.

4.2. Step 2: design of the virtual environment

The core of the proposed approach concerns the design and development of hypothetical scenarios exploiting the extended reality. This approach is specifically developed to obtain an extended reality-based CE to assess the impact of offshore wind turbines in the historic center, and it consists of additional four sub-parts as shown in Fig. 3: i) *On site survey*, ii) *3D modelling*; iii) *Photomontage*; iv) *VR viewer*.

The *on-site survey* has a dual purpose, firstly to acquire 360° images (e.g. through go pro max) showing the view of the sea from the historical center in order to enable subsequent photo editing of various scenarios of wind turbines, and secondly to collect historical data and information on artistic and architectural assets in the urban context. Such data acquisition are useful to insert, in the virtual environment, proper information regarding the main architectural and historical assets to show users with useful information and orient themselves within the context.

The *3D modelling* are achieved based on the results of the first step to be consistent with the definition of the hypothetical scenarios. Wind turbines of various types and sizes are modeled using CAD software

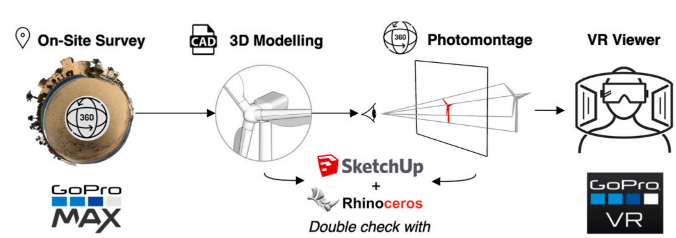

Fig. 3. The four sub-part of the step 2 (Design of the virtual environment).

(such as Rhino, SketchUp) to satisfy all possible combinations defined in the hypothetical scenarios. Furthermore, the moderation technical specifications follow the suggestions described in Sangiorgio et al. (2020, 2022) to keep the file size of the 3D model small such to avoid a potential slowdown during visualization.

The *Photomontage* allows to merge the 360° images and the 3D models in one virtual environment. This step exploits various software, techniques and approaches to allow the user to visualize, in an immersive environment, the presence of offshore wind turbines superimposed on the real context, through the use of specific photomontages. In particular, the evaluation of the perspective is carried out and verified by a double comparison between different 3D software (such as SketchUp or Rhinoceros). During the *Photomontage* the virtual environment is enriched with information indicating the presence of buildings of particular artistic or architectural value such as castles, churches or cathedrals. Beside providing valuable information that enhances the user's understanding of the urban context, these pieces of information are also helpful for local users to navigate within the virtual environment.

Finally, the *VR viewer* allows to test the achieved VR and to report any necessary display errors to be fixed. Note that the proposed approach allows for achieving an immersive digital environment through 360° photos of the physical environment. In addition, the procedure allows to overlay digital information onto the physical environment. Consequently, the resulting approach is a hybrid virtual/augmented reality. To this end, the current approach can be regarded as an extended reality-based CE.

4.3. Step 3: integration of the extended reality with CE

The CE integration with the extended reality can be built using the hypothetical offshore wind farm scenario as described in section 2.2. Starting by the plan of the layout of the virtual offshore wind farm, it is necessary to consider the number of turbines, their positioning, and any surrounding landscape elements. To this aim the use of 3D modeling software help visualizing the layout. Of relevant interest, is the collection of data related to wind turbines, such as dimensions, power output, and efficiency.

In order to build the choice alternatives of offshore wind farms, it is essential to select a VR platform capable of accommodating the 3D models of wind turbines, the surrounding environment, and any additional structures (including the various attribute levels for direct information access about the alternatives).

To this aim, the open access VR platform KUULA is used to test the extended reality offshore wind farm scenario extensively to identify and fix any issues or improvements. Gathering feedback from users, some necessary adjustments can be made to enhance the experience.

Once the scenario results are satisfactory, KUULA platform creates a link and distribute it through app stores, VR platforms, or even showcase it directly on the Qualtrics survey platform within the choice sets.

To ease the virtual experience, it is important to provide appropriate instructions or guidance during the CE and within the extended reality experience.

4.4. Step 4: the survey

Structuring the survey about wind energy perception involves careful planning and organization of questions to collect relevant and comprehensive data. Firstly, it is important to clearly outline the objectives of the survey. In addition, it is relevant to decide what specific aspects of wind energy perception to assess, such as attitudes towards wind energy, concerns, knowledge levels, or willingness to support wind energy projects. The survey generally starts with a brief and engaging introduction that explains the purpose of the survey, assures confidentiality, and encourages participation.

The structure of the questionnaire includes a section that gathers basic demographic information about respondents, such as age, gender, education level, occupation, and location. This data helps in analyzing responses and understanding any variations based on demographic factors. The CE section can be anticipated by questions about wind energy awareness and knowledge, attitudes and perceptions, concerns and barriers, benefits and support of wind energy, communication and information, and preferred locations and incentives. Visualization is the key aspect to gauging respondents' overall attitudes towards wind energy. Data generally aim to assess perceptions related to environmental impact, cost-effectiveness, reliability, and potential benefits to the local community. If possible, the inclusion of visual representations or extended reality simulations of wind energy projects is necessary to better assess respondents' perceptions and explore any concerns or barriers that respondents may have regarding the adoption of wind energy. The integration of extended reality into CE enables the exploration of trade-offs among the perceived benefits of wind energy, (such as reduced carbon emissions, job creation, or energy security) and the visual concerns on the landscape environment. It also assesses respondents' support for wind energy projects.

Before launching the survey, a pilot test is conducted with a small group of respondents to identify any issues with question clarity or survey flow. After collecting the data, the responses are analyzed using appropriate statistical methods. The analytics of a CE involves analyzing the collected data from the survey to estimate the relative importance of different attributes and how they affect decision-making. These models estimate the probability of choosing a particular option as a function of the attributes presented in the scenarios and the respondent's individual characteristics. The results of the analysis can be used to estimate the willingness to pay/accept (WTP/WTA) for different attributes, to identify segments of the population with different preferences, and to simulate the effects of hypothetical policy changes or product improvements.

These estimates can then be used to inform decision-making in areas such as product design, pricing, and policy development.

5. Application in the historic center of Manfredonia

The section describes into details the steps used in the new approach applied to the historic center of Manfredonia.

5.1. Choice experiment design (application of step 1)

The focus of the present CE study is to evaluate the perception of an offshore wind farm project. Through consultations of recent offshore wind energy project proposals, as well as conducting focus group discussions with the local population, several elements that can either drive or hinder acceptance of the offshore wind farm project have been identified.

(1) Visual impact affecting environmental and touristic features of Manfredonia and its surroundings, which may be influenced by attachment or identity values. These are places that hold special importance for the community due to their environmental significance and as recreational destination.
(2) Visual impact touching cultural and archeological points of interest, particularly in sites hosting historical monuments and memories. These sites may not have identity values, but they could have potential option values for cultural preservation.
(3) Economic benefits linked to the wind energy project, which might affect individuals or private entities within the local community. These benefits could include private or public benefits such as energy bill savings or various services or programs that directly impact the well-being of the community.

The above elements are taken into account in terms of attributes for the CE as summarized in Table 1.

Table 1
Attributes and levels.

Attribute Name	Definition and Levels
Visual impact	This attribute refers to the aesthetical impact of a 160 MW offshore wind farm in the surrounding landscape according to two different combinations of number and dimension of the turbines. The corresponding levels are: **LOW**: 10 turbines of 16 MW with a height of 380 m **HIGH**: 20 turbines of 8 MW with a height of 300 m
Distance from shore	This attribute refers to the distance in kilometers of the offshore wind farm from the shore according to existing projects. The corresponding levels are: **15 km, 20 km, 25 km.**
Compensation amount	This attribute refers to the percentage of the economic compensation for the social damage for the local community computed on the value of energy produced. The corresponding levels are: **< 1%; 1–3%; >3%.**
Compensation distribution	This attribute refers to the type of compensation for the local community. The corresponding levels are: **REDUCTION OF BILL COSTS FOR FAMILIES REDUCTION OF BILL COSTS FOR COMPANIES IMPROVEMENT OF PUBLIC WORKS/SERVICES**

1. Visual impact on a valuable coastal location with cultural interest, with two levels of density: (a) high number of turbines, (b) low number of turbines.
2. Distance from shore, with three levels of visibility: (a) close to the coast and well-visible, (b) far away/not well-visible from the coast, and (c) far away/not visible from the seaside.
3. Economic compensation of social damage (percentage of the value of the energy produced), with three levels of percentage: low, medium and high.
4. Compensation distribution, with three levels: (a) reduction in energy bill for families, (b) reduction in energy bill for companies, (c) additional public services.

These attributes, levels, and their pictorial representations were carefully assessed and revised in pre-tests to ensure clarity and understanding by the respondents. The CE is consequently designed with three choices, where respondents compare two alternative scenarios and the status quo. This is standard in CE analysis to keep the survey straightforward and avoid an excessive cognitive burden on the participants. This approach allows for a simpler yet informative assessment of respondents' preferences and perceptions regarding the offshore wind farm project.

The experimental design is modeled assuming the status quo (i.e. the landscape as is) and two alternatives of offshore wind farm, with the following utility functions:

$$U(alt1)= \beta_0 + \beta_{visual} * NUM[10,20] + \beta_{dist} * DIST[15,20,25] + \beta_{comp} * COMP[1,2,3] + \beta_{distrib} * DISTRIB\,[1,2,3] \tag{5}$$

$$U(alt2)= \beta_0 + \beta_{visual} * NUM[10,20] + \beta_{dist} * DIST[15,20,25] + \beta_{comp} * COMP[1,2,3] + \beta_{distrib} * DISTRIB\,[1,2,3] \tag{6}$$

This procedure results in a D-efficient design with 0.014 of error component designed in 27 pairwise comparisons of the offshore wind farms alternatives, allowing for a comprehensive analysis of different combinations and trade-offs among the attributes (Table A1).

To enhance the experimental design, the 27 choice situations of offshore wind energy are randomly split into three blocks. Each block consists of nine choice sets, with each set comprising two alternatives of offshore wind farms and an opt-out alternative representing the current status quo. The inclusion of the status quo (existing condition) or a baseline scenario is crucial for interpreting the welfare implications of the estimates and ensuring their consistency with demand theory, as outlined by Louviere et al. (2000), Bennett and Blamey (2001), and Bateman et al. (2003).

5.2. Extended reality design (application of step 2)

The design of the extended reality is achieved by following the four sub-steps defined in subsection 2.2.

Firstly, the *on-site survey* involves capturing over 50 images (360° each) using a GoPro Max camera, which owns the following specifications: Photo Resolution of 16.6 MP with size of 5760 × 2880, Dual Fisheye (Wide 8.9 mm Focal Length). Among the acquired images, the best one is selected for the subsequent *Photomontage*. In particular, the selected photo allows for the best representation in terms of significance and presence of wind turbines which are visible from the beach of the historic centre of Manfredonia. From this beach, it is also visible the most important and distinctive constructions of the city, including the Swabian Angevin Castle, the ancient port, and the old town (upper part of Fig. 4).

Secondly, the *3D modeling* is accomplished by utilizing the turbine dimensions defined in step 1, encompassing turbines with heights of 300 m and 380 m respectively. The *3D modeling* is provided by the software Rhinoceros (Version 7.28.23058.03002, 2023-02-27), and Sketch UP make (Version January 16, 1451).

Thirdly, a total of 55 *Photomontage* are completed to achieve the VR environment of all the defined scenarios grouped in the three Blocks (Block 1 = 18 photos; Block 2 = 18 photos; Block 3 = 18 photos; Status quo = 1 photo). Note that in every scenario, the *Photomontage* is performed in order to include the information about attributes and levels directly inside the extended environment. The *3D modelling* and *Photomontage* are carried out with the use of Rhinoceros (Version 7, 7.28.23058.03002, 2023-02-27), Sketch UP make (Version January 16, 1451), Anteprima (Version 11.0 (999.4)) and Photoshop 2022 (Version 32.5.1). Finally, the 55 *Photomontage* are displayed by means of the software go pro VR Player (Version 3.0.5).

Fig. 4 shows one of the 55 *Photomontage* displaying 10 wind turbines of 380 m height at a distance of 15 km from the cost. In particular, the upper part of the figure shows an extract of the virtual environment, while the bottom part of the figure shows an excerpt of the extended reality where it is possible to see the above-mentioned 10 wind turbines. It is worth noting that the resulting immersive digital environment is based on the 360° photos of the physical environment, but includes overlaid digital information such as wind turbines (3D models), data on the scenario (attributes and levels) and information about the surrounding context (indication of the castle, port and historic center).

5.3. The resulting hybrid approach extended reality-based CE (application of step 3)

The CE survey starts by gathering information on the current situation of bill costs, energy-related concerns, knowledge, and perceptions regarding alternative energy production technologies, particularly wind energy production. Following this, respondents are provided with a description of the attributes employed in the experiment. In particular, nine choice sets are presented, and for each set, respondents are asked to indicate their preferred option between two offshore wind farms and the status quo.[1]

The CE survey was conducted during December and January 2023 in Italy. The survey employed online interviews distributed by Qualtrics to a panel of 507 respondents selected from the Italian population. A quota sampling approach was employed to ensure the representativeness of the sample in terms of gender, age and geographical distribution. A total of 504 respondents (99% of the sample) participated in the survey, resulting in a total of 4536 choices made among the three scenarios.

[1] As an example, the interested reader can visit the following link to see one of three scenarios defined in a choice set (e.g. Alternative 1 of Choice Set 2). URL at: *https://kuula.co/share/NRzYY?logo=1&info=1&fs=1&vr=0&sd=1&thumbs=1&inst=it*.

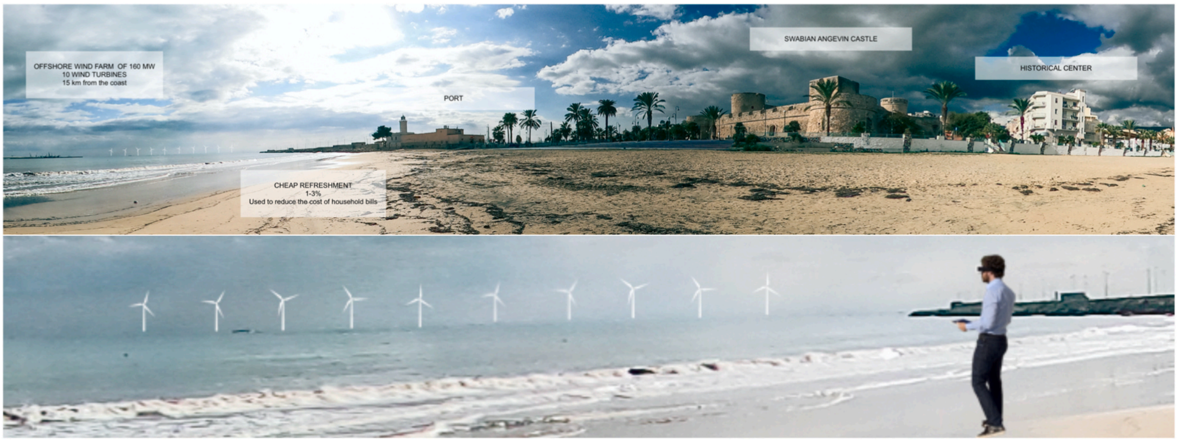

Fig. 4. Extract of the virtual environment (upper part), focus on 10 wind turbines (bottom part).

Considering the estimated sample size of 47 observations from the efficient design (Table A1), the obtained sample results consistent and statistically significant. Fig. 5 illustrates an example of the resulting hybrid approach extended reality-based CE.

Alongside the CE, the final part of the survey retrieves social, demographic, and economic data from the respondents. This includes information such as age, gender, education level, job, and residency place. The descriptive statistics for key socio-demographic variables can be found in Table A2.

6. Analysis, results and discussion (application of step 4)

The obtained results, as described in the present section, demonstrate how the employed methodology enables the acquisition of respondents' perceptions regarding the impact of offshore wind turbines on the historic center of Manfredonia. In addition, the Multinomial Logit model other than presenting the estimated trade-offs, allow to obtain the marginal WTA for compensation.

6.1. Respondents' perception of energy knowledge

The data from the survey reveals that a substantial proportion of respondents, approximately 89%, observed an increase in their energy bills. Out of these, 62% reported a rise of up to 50% compared to the previous year. Moreover, a notable 19% of respondents witnessed a significant increase exceeding 75% in their bill costs. Fig. 6 shows the main reasons perceived by respondents for the increased bill costs. Notably, the highest percentage of respondents expressed their concerns about Italy's dependence on other countries for energy sources (34%). This is followed by worries related to the recent outbreak of war in Ukraine (28%). These findings highlight the significance of energy security and the geopolitical context in influencing public perception of rising energy costs. Strojny et al. (2023) further support these results and note some variations in energy security perceptions. They suggest that the conventional "supply concept" of energy security is evolving into an approach where energy becomes a catalyst for profound changes in societal systems. This includes altering consumption habits, reducing overall energy consumption, and driving shifts in economic structures through energy efficiency and environmental regulations. Such insights can be crucial in shaping energy policy and addressing public concerns to ensure a stable and sustainable energy future and the present work contributes to this scope.

Fig. 5. Respondent during the use of the extended-reality-based CE.

At the same time, the survey results indicate that only a small percentage of respondents, 8%, believe that the low investment in certain alternative sources of energy production affects energy costs (Fig. 6). This finding may be explained by the high perception of the presence of renewable power plants in the areas where respondents live. Indeed, a significant number of respondents reported the implementation of solar and wind energy in their living areas, with approximately 59% having solar energy facilities and 30% having wind energy facilities, as shown in Fig. 7.

The presence of these renewable energy installations in respondents' living areas could lead to a perception that the investment in such technologies is already adequate, hence the lower concern about its impact on energy costs. This highlights the role of local experiences and direct exposure to renewable energy sources in shaping public attitudes and perceptions towards their costs and benefits. As the adoption of renewable energy technologies increases, it is essential to continue monitoring public perceptions and awareness to foster continued support for sustainable energy solutions. A similar finding can be associated to the "not-in-my-backyard" (NIMBY) syndrome that is largely discussed in literature as driver of social acceptance of renewable energy projects (Walker et al., 2018; Swofford and Slattery, 2010; Bell et al., 2005). However, the present work does not meet a real obstacle to renewables, rather it seems to be more in line with the "not in my backyard but not far away from me" phenomenon identified more recently by Guo et al. (2015) and San Martin (2023).

On the other hand, results demonstrate that a significant majority of respondents, approximately 79%, consider investment in renewable energy technologies as necessary to overcome the energy emergency. This highlights the strong support for renewable energy as a viable solution to address energy challenges and move towards a sustainable energy future, as depicted in Fig. 8. In contrast, a considerable number

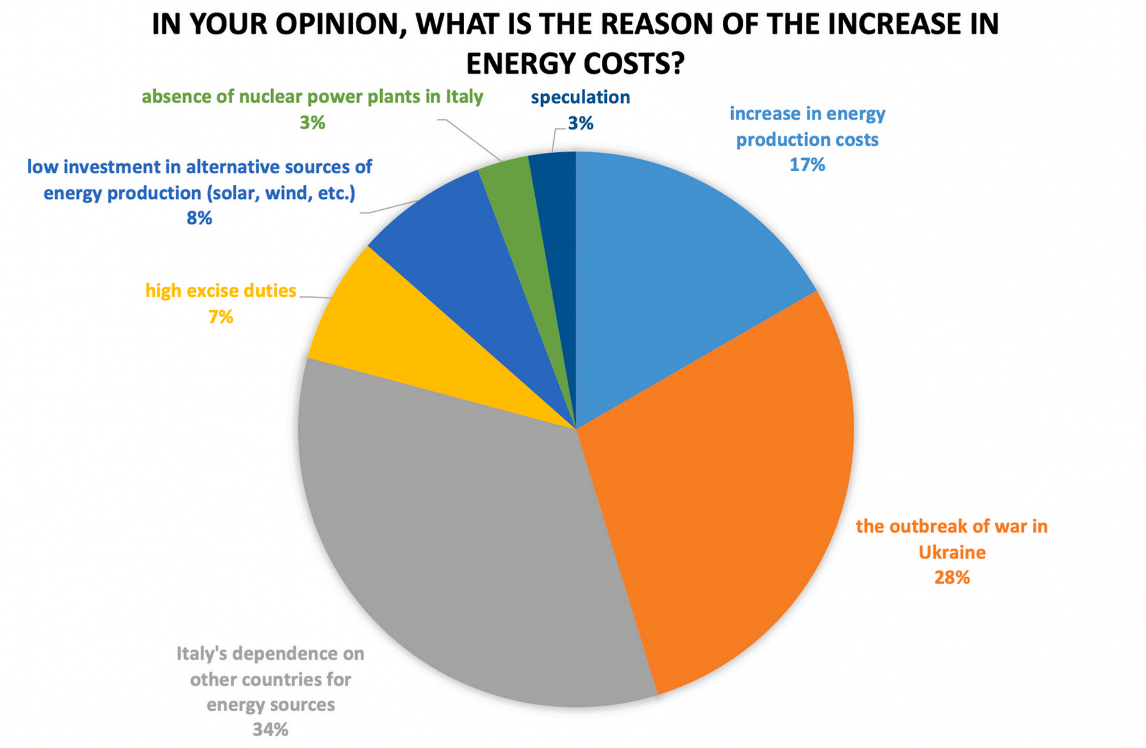

Fig. 6. Respondents' perception about the reasons of the energy costs increase.

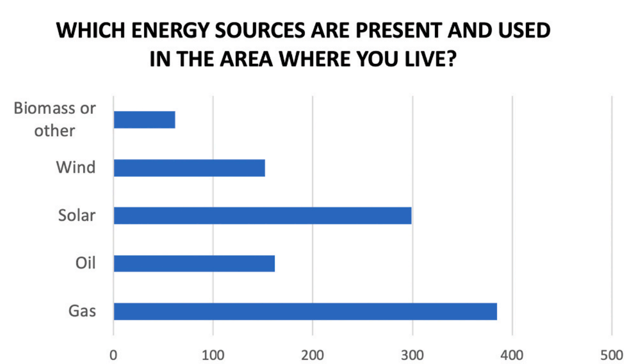

Fig. 7. Respondents' perception of different energy power plants presence in the territory.

of respondents, about 22%, view the investment in nuclear power plants as a useless or harmful initiative (Fig. 8). This indicates a higher level of skepticism about nuclear energy as a potential solution to the energy emergency. The contrasting attitudes towards renewable energy and nuclear power reflect the divergent opinions held by the public on different energy sources. Despite the literature (Lee et al., 2013) contributes with some potential solutions for using nuclear power safely to involve moving the conventional nuclear power plant, the above results emphasize the importance of considering public preferences and concerns in energy policy decisions.

These outcomes underscore the need for governments and policymakers to take into account public attitudes and preferences when formulating energy strategies. Public acceptance and support are crucial factors in implementing successful and sustainable energy policies that can effectively address energy challenges and foster a transition towards cleaner and more reliable energy systems.

The findings presented above validate the citizens' strong demand for the further development of renewable energy production due to its perceived lower pollution compared to fossil fuels, as indicated in Fig. 8. However, it is crucial not to overlook the public concerns related to renewable energy technologies and their potential impact on the landscape. Notably, 65% of respondents express their worries about wind power plants, whereas 57% are concerned about solar power plants (Fig. 9). These results highlight the importance of addressing public apprehensions and perceptions when considering the implementation of renewable energy projects, particularly those involving wind and solar power, to ensure successful and sustainable energy transitions. Public engagement and communication efforts play a crucial role in addressing these concerns and building support for the transition to cleaner energy sources.

In terms of tourism impact and pollution, respondents perceive solar and wind sources mostly in a similar way (Fig. 9). On the other hand, in terms of costs, approximately 23% of respondents consider biomass as the most expensive renewable energy source, followed by solar (20% of respondents) and wind energy (12% of respondents).

The above results suggest that while solar and wind are favorably perceived in terms of their environmental impact, there is a perception that solar energy may be relatively more expensive compared to other renewable sources.

In general, respondents express a favorable attitude toward the use of renewable energy sources for energy production. Moreover, no substantial differences between respondents' preferences for on-shore and off-shore wind farms exist. In both cases, respondents show, on average, a favorable feeling toward the development of wind technology.

The survey also reveals that wind farms can bring economic benefits to the population. This view is favorably expressed by the majority of respondents (90%).This indicates widespread approval and positive sentiment towards wind energy projects. Moreover, a substantial proportion of respondents (82%) show support for municipal policies that allocate economic resources to build wind farms, indicating a willingness to invest in renewable energy initiatives at the local level.

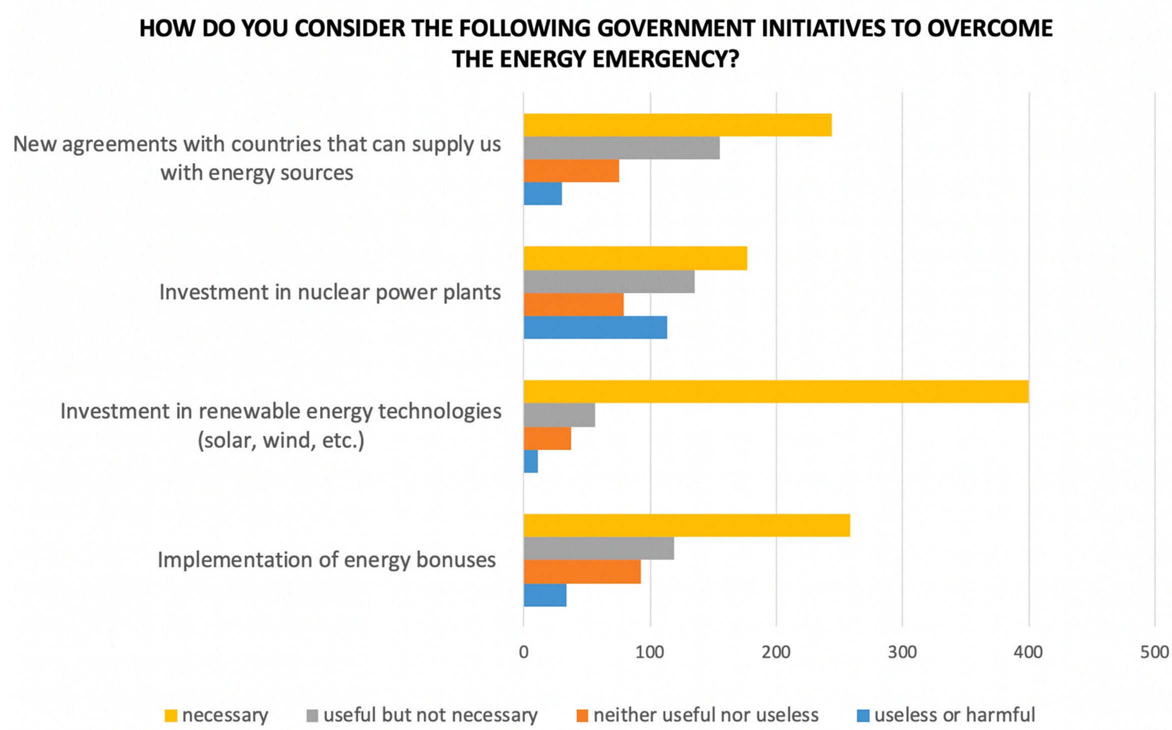

Fig. 8. Respondents' perception of the government initiatives to overcome the energy emergency.

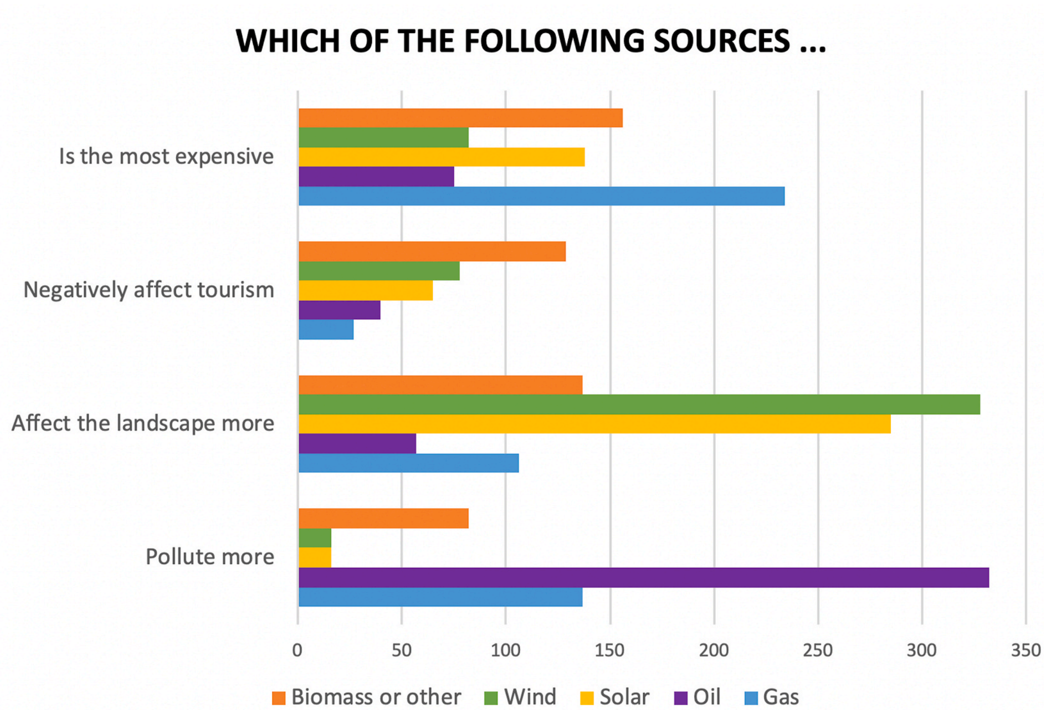

Fig. 9. Respondents' perception of the energy sources.

Among the economic benefits perceived by respondents from the installation of a wind farm, the following receive the highest levels of support.

- Increase in employment opportunities: Approximately 92% of respondents consider this as a significant economic benefit of wind farms, indicating the potential for job creation in the local community.
- Tax deductions on municipal taxes: About 91% of respondents support the idea of tax deductions on municipal taxes as a benefit from wind farm installation, suggesting the potential for reduced tax burdens for residents.

- Access to new services (e.g., free transport): Approximately 88% of respondents view the availability of new services, such as free transport, as a positive economic impact of wind farms, which could improve the quality of life of residents and visitors.

These findings indicate that the public perceives tangible economic advantages from wind energy projects, which can contribute to fostering public support for the development and implementation of such initiatives at the municipal level and highlight the positive perception of wind energy as a potential driver of economic growth, job creation, and enhanced public services. The support for municipal policies aimed at promoting wind energy projects indicates the public's interest in sustainable energy initiatives that can bring tangible benefits to the local community.

According to Fig. 10, the top five initiatives that can be carried out on the territory from revenues deriving from the installation of wind plants are as follows (in descending order of support).

- Guaranteeing residents, a cap price for electricity (67%). This slightly drops to 65% of respondents when the initiative is targeted to businesses.
- Making funds available to the Municipalities for the improvement of local infrastructures (66%).
- Providing a constant plan for monitoring the environmental impact of the plants (64%).
- Developing a territorial electric public transport system (64%).

Regarding the initiatives having an impact on tourism and its promotion, the majority of respondents consider them necessary for a further development of the area. However, for more than one third of respondents (33–35%) these initiatives are seen as useful but not strictly necessary.

These findings indicate strong support among respondents for initiatives that focus on local benefits and improvements in areas where wind plants are installed. However, an interesting work of Munday et al. (2011) highlights that wind farm developers commonly offer various types of community benefits to areas impacted by these projects but these benefits have not yet translated into substantial economic development tools for these communities. They conclude the paper by proposing potential strategies to enhance economic outcomes from wind farm developments and in the present study we try to gain insight into respondents' perceptions concerning certain potential strategies. The public's interest in guaranteeing a cap price for electricity and investment in local infrastructure reflects a concern for community well-being and economic development. Similarly, the emphasis on monitoring environmental impacts and the development of electric public transport systems show a commitment to eco-friendly transportation solutions.

Public opinion on tourism-related initiatives indicates a recognition of the importance of tourism for local economies, but also suggests the need for balanced decision-making to ensure that tourism promotion aligns with other community priorities.

In this context, information plays a crucial role in shaping public perception of wind energy development and the associated benefits. A vast majority of respondents (92%) consider information as an essential factor in understanding the installation of wind energy projects.

Regarding the responsibility for communication and information provision, governmental institutions are seen as primary actors. Specifically, 74% of respondents attribute the responsibility to national-level governmental institutions, highlighting the significance of national-level communication efforts. European-level institutions are also perceived as important information providers, with 60% of respondents expecting them to play a role in communication plans.

At regional and local levels, 43% and 28% of respondents, respectively, also consider governmental institutions responsible for providing

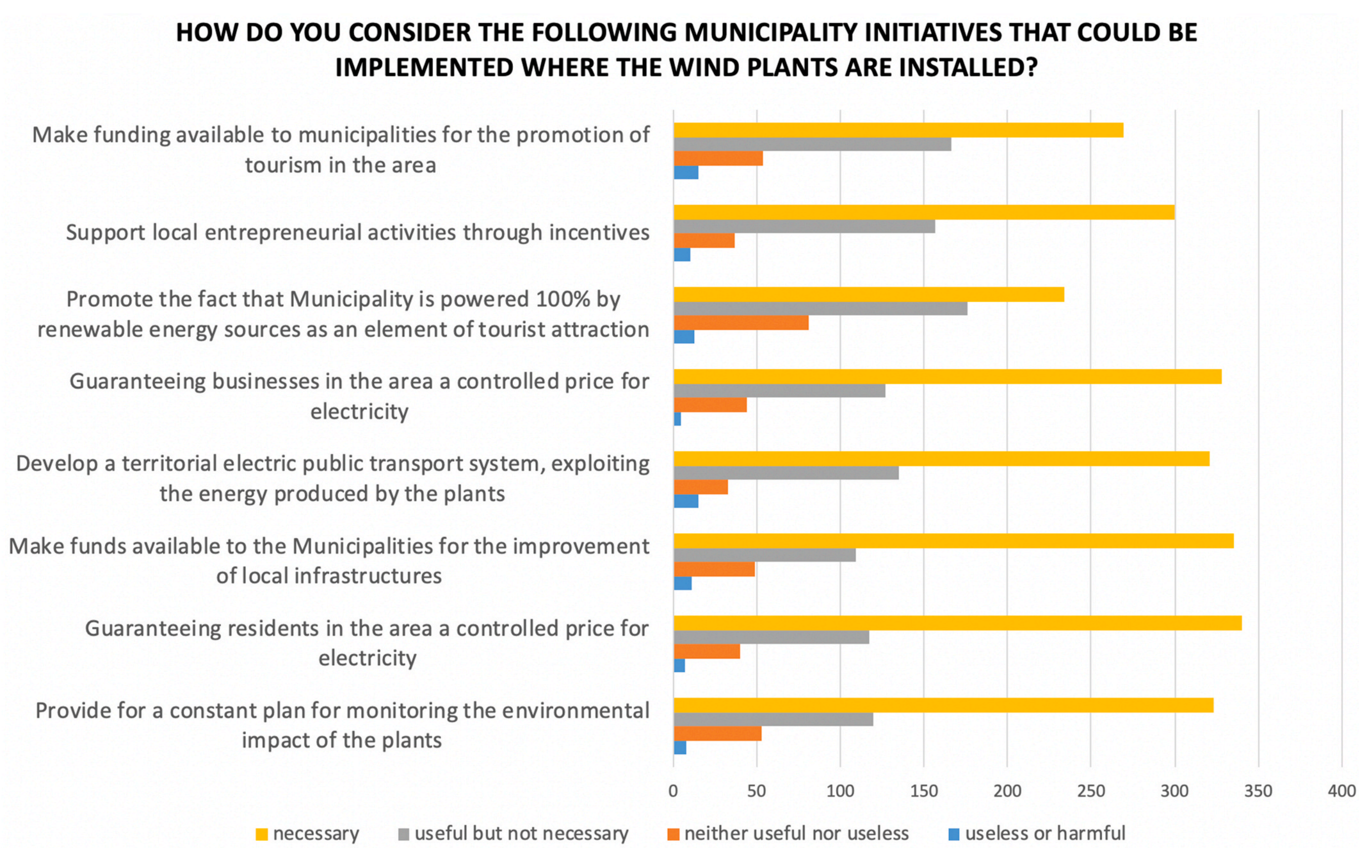

Fig. 10. Respondents' perception of potential initiatives following the implementation of wind plants.

the diffusion of proper information.

These findings emphasize the role of governmental agencies and institutions in providing effective communication and information strategies about wind energy developments to the public, which aligns with the conclusions drawn by Caporale and De Lucia (2015). Public acceptance and support for such projects are likely to increase if governmental bodies are proactive in sharing transparent and accurate information, addressing potential concerns, and engaging with the public to build mutual trust and understanding.

6.2. Multinomial logit model estimates

CEs data indicate that, out of the total number of choices made by respondents in the survey, only 696 choices (approximately 5% of the total) refer to the status quo. This suggests that respondents are keen towards the implementation of the offshore wind farm over the status quo.

Table 2 shows the estimated results of the Multinomial logit model (MNL), providing insights into the determinants of choice and the significance of various attributes in shaping respondents' preferences for the offshore wind farm.

The choice model is estimated using the NLOGIT6 software. The p-values of the estimated coefficients of each attribute (explanatory variables) indicate that these are statistically significant at the 1% level, except for the 'Compensation distribution' attribute.

The estimated signs of the coefficients for 'Visual impact', 'Distance from shore', and 'Compensation amount' are all positive. This implies that: i) The higher the turbines' density, the higher is the utility of respondents. Similarly can be said for the proximity of turbines from the coast. In other words, respondents perceive a higher utility level for wind turbines located further away from the coast and in greater numbers than the status quo. ii) The utility of respondents increases as the economic compensation for the social damage to the local community increases. This is reasonable as higher compensation can offset the negative contribution of social costs to utility, leading to a more favorable perception of the offshore wind farm project.

These findings provide valuable insights into how various attributes influence respondents' utility and preferences in the CE. They indicate that factors such as visual impact, distance from the coast, and compensation amount play significant roles in shaping public acceptance and support for offshore wind energy projects. As early as 2009, Ladenburg cautioned against placing offshore wind farms too close to the coast and concluded that the future acceptance of such wind farms is closely tied to the location of existing and new offshore installations. Following Ladenburg's study, various contributions have highlighted that the potential visual impact on coastal areas has become a significant concern in the development of offshore wind facilities around the world (Sullivan, et al., 2013; Maslov et al., 2017; Kim et al., 2019). To determine the best locations for offshore facilities, it is crucial to have precise information about how distance influences the visibility of wind turbines.

To this aim, the use of extended reality technology in the choice scenarios significantly improves the results and understanding of the landscape impact of the off-shore wind farm because it provides a more accurate, immersive, and contextually relevant experience for respondents. It enhances the quality of data collected and allows researchers to gain a deeper understanding of the factors influencing public perception and acceptance, ultimately leading to better-informed energy policy decisions and successful implementation of renewable energy projects.

Table 2
Multinomial logit model estimates of offshore wind energy.

Variable	Coefficient	St. error	p-Value	95% Confidence Interval
Visual impact	0.011***	0.003	0.000	[0.005] [0.017]
Distance from shore	0.028***	0.003	0.000	[0.023] [0.034]
Compensation amount	0.093***	0.019	0.000	[0.056] [0.130]
Compensation distribution	−0.008	0.019	0.679	[-0.046] [0.030]
Log-Likelihood	*−4625.8977*			
Obs	*4536*			

Source: Our elaborations. ***, **, * => Significance at 1%, 5%, 10% level.

6.3. Marginal WTA compensation estimates

Finally, the marginal willingness to accept compensation (MWTAC) estimates for an increase or a decrease in the level of each attribute can be derived through Equation (5).

$$MWTAC = -\frac{\partial V}{\partial x^*} \Big/ \frac{\partial V}{\partial price} = -\frac{\beta_*}{\beta_p} \tag{5}$$

Where β_* and β_p are the marginal utilities of attribute V and *price*, respectively. When the utility function is specified to be linear in parameters, the marginal utility of an attribute is equal to its coefficient, which means that MWTAC is given by the negative of the ratio of the coefficients for attribute V and *price*.

In Table 3, the MNL results from Table 2 are used to estimate the MWTAC for the statistical significant attributes of 'Visual impact' and 'Distance from shore'.

Computing marginal WTA measures is a convenient and useful way to compare attribute estimates. The values presented in Table 3 can be interpreted as the environmental costs for the social damage to the local community resulting from the development of an offshore wind farm in Manfredonia.

The corresponding MWTAC estimates for an increase in the offshore wind farm size (in terms of number and height of turbines) and the distance from the shore are −0.119 and −0.304 respectively. Considering that the 'Compensation amount' attribute refers to the percentage of the economic compensation computed on the value of energy produced, the computations of the MWTAC in Euros proceeds first by retrieving data on energy costs in Italy from official statistical sources, and second by multiplying the energy costs by the obtained estimates of the MWTAC of the interested attributes. According to the Gestore Mercati Energetici (GME, https://www.mercatoelettrico.org/en/), the average cost of energy in Italy in 2023 is about 110 €/MWh. As a consequence, the MWTAC for 'Visual impact' and 'Distance from shore' expressed in Euros are obtained as follows:

$$\text{Cost of 1MWh of energy produced} * 0.119\ (\text{MWTAC for visual impact}) = 110 * 0.119 = 13.09€$$

$$\text{Cost of 1MWh of energy produced} * 0.304\ (\text{MWTAC for distance from shore}) = 110 * 0.304 = 33.44€$$

Specifically, the WTA compensation decreases by approximately 13€ for every one-point increase in the visual impact of the wind farm. This

Table 3
MWTAC estimates of off-shore wind energy attributes (WALD procedure).

Variable	Coefficient	St. error	p-Value	95% Confidence Interval
Visual impact	−0.119***	0.045	0.008	[-0.207] [-0.030]
Distance from shore	−0.304***	0.076	0.000	[-0.454] [-0.155]
Wald Statistics	*16.623*			
Prob. from Chi-squared	*0.001*			

*Source: Our elaborations. ***, **, * => Significance at 1%, 5%, 10% level.*

means that as the visual impact of the wind farm becomes more significant, respondents are less willing to receive compensation to mitigate the negative effects. Similarly, the MWTAC decreases by about 33€ for every one-point increase in the distance of the wind farm from the shore. As the wind farm is located further away from the coast, respondents are less willing to receive compensation, suggesting that proximity to the shore is an important factor influencing perceptions of the wind farm's impact.

Four studies were identified by Wen et al. (2018) that assessed the marginal values of relocating offshore wind farms to various distances. All these studies utilized Willingness to Pay (WTP) as the indicator of welfare and collectively identified an average linear growth rate of WTP with distance spanning from 8 km to 50 km (Ladenburg and Dubgaard, 2007, 2009; Ladenburg and Möller, 2011; Krueger et al., 2011; Westerberg et al., 2013).

Conversely, of the 12 studies identified by Wen et al. (2018) estimating the marginal values of wind farm size (considering the number of the turbines), only three of them utilized the WTA as the indicator of welfare mostly focused on the size of 2–50 turbines. Specifically, García et al. (2016) show the most similar result with our study with a marginal value of 10.88 $/household/year/turbine spanning from 9 to 18 turbines. Not far offs results the marginal value of 12 $/household/year/turbine spanning from 9 to 40 turbines by Brennan and Van Rensburg (2016). Instead, Dimitropoulos and Kontoleon (2009) show a higher marginal value in a wider range of turbine number (32.4 $/household/year/turbine and 2–40 turbines).

7. Conclusion

The present research underscores the importance of addressing public apprehensions and perceptions, particularly regarding wind power projects, to ensure successful and sustainable energy transitions. While wind energy is perceived as cost-effective, it is also considered to have a significant impact on the landscape, particularly related to important historic and cultural centers.

The study is conducted in the city of Manfredonia, a representative touristic city of the southern Italy. In this context, the work provides insights into the public's perception of wind energy as a potential driver of economic growth, job creation, and improved public services, which can foster support for such initiatives at municipal level.

To minimize potential biases from using non-realistic visualization tools in assessing the visual impact of offshore wind farms, the present study introduced a novel approach, such as the extended reality-based CE. According to the first and second objectives of the study, it has been provided an exhaustive and structured methodology approach and offered a direct application that significantly improves the understanding of the landscape impact of offshore wind farms, providing a more accurate and immersive experience for respondents.

The attributes considered in the CE covered critical factors such as visual impact, distance from the shore, economic compensation, and distribution of benefits from compensation. Our findings illustrate that the inclination to establish an offshore wind farm over maintaining the status quo is prevalent across various hypothetical scenarios, highlighting the potential acceptance of such projects in Manfredonia. Respondents' utility increases with greater distances of wind turbines from the coast. Similarly, when economic compensation for social damage to the local community is higher, the obtained outcomes suggest the importance of strategic project placement and compensation mechanisms.

Moreover, the willingness to accept compensation decreases with higher visual impact and greater distance of the wind farm from the shore. This insight is essential for developing compensation strategies that align with public expectations and contribute to smoother project implementation.

The obtained results answer to the third objective of the present study and highlight the complex interplay of various factors influencing public perception and acceptance of offshore wind energy developments.

The extended reality-based CE provides valuable insights into how the above factors influence respondents' decisions and can aid in formulating effective policies and communication strategies. By addressing concerns related to visual impact, ownership, distribution of benefits, and considering both public and private benefits, energy projects can be better tailored to meet the needs and preferences of the local community, fostering a positive perception from communities and successful implementation.

CRediT authorship contribution statement

Diana Caporale: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization, Writing - original draft. **Valentino Sangiorgio:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization, Writing - original draft. **Caterina De Lucia:** Methodology, Supervision, Resources, Writing - review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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APPENDIX

Table A1
Efficient design estimation (D-error)

MNL efficiency measures				
D error	0.0144			
A error	0.0407			
B estimate	91.58			
S estimate	47.33			
Prior	Visual impact	Distance from shore	Compensation amount	Compensation distribution

(*continued on next page*)

Table A1 (*continued*)

MNL efficiency measures				
Fixed prior value	−0.03	0.04	0.08	−0.01
Sp estimates	9.34	7.73	47.33	30.16
Sp t-ratios	0.64	0.70	0.28	0.36

Design

Choice sets	Alt.	Visual impact	Distance from shore	Compensation amount	Compensation distribution	Block
1	1	High	25 km	1–3%	improvement of public work/serv.	3
	2	Low	15	1–3%	reduction bill cost for families	3
2	1	High	15	<1%	reduction bill cost for companies	2
	2	Low	25	3%	reduction bill cost for companies	2
3	1	Low	20	3%	reduction bill cost for families	2
	2	High	20	<1%	improvement of public work/serv.	2
4	1	High	15	3%	reduction bill cost for companies	3
	2	Low	25	<1%	reduction bill cost for companies	3
5	1	High	20	3%	reduction bill cost for families	1
	2	Low	20	<1%	improvement of public work/serv.	1
6	1	Low	20	1–3%	reduction bill cost for families	1
	2	High	20	1–3%	improvement of public work/serv.	1
7	1	Low	15	3%	reduction bill cost for companies	3
	2	High	25	<1%	reduction bill cost for companies	3
8	1	Low	20	1–3%	improvement of public work/serv.	1
	2	High	20	1–3%	reduction bill cost for families	1
9	1	Low	25	1–3%	reduction bill cost for families	3
	2	High	15	1–3%	improvement of public work/serv.	3
10	1	High	20	3%	improvement of public work/serv.	1
	2	Low	20	<1%	reduction bill cost for families	1
11	1	Low	15	1–3%	reduction bill cost for families	1
	2	High	25	1–3%	improvement of public work/serv.	1
12	1	High	15	<1%	reduction bill cost for families	3
	2	Low	25	3%	improvement of public work/serv.	3
13	1	Low	20	<1%	reduction bill cost for companies	1
	2	High	20	3%	reduction bill cost for companies	1
14	1	Low	25	3%	reduction bill cost for companies	3
	2	High	15	<1%	reduction bill cost for companies	3
15	1	High	25	1–3%	reduction bill cost for families	1
	2	Low	15	1–3%	improvement of public work/serv.	1
16	1	High	25	<1%	improvement of public work/serv.	3
	2	Low	15	3%	reduction bill cost for families	3
17	1	Low	25	<1%	reduction bill cost for families	3
	2	High	15	3%	improvement of public work/serv.	3
18	1	Low	15	<1%	improvement of public work/serv.	2
	2	High	25	3%	reduction bill cost for families	2
19	1	High	20	3%	reduction bill cost for companies	3
	2	Low	20	<1%	reduction bill cost for companies	3
20	1	High	15	1–3%	reduction bill cost for companies	2
	2	Low	25	1–3%	reduction bill cost for companies	2
21	1	High	20	<1%	reduction bill cost for families	2
	2	Low	20	3%	improvement of public work/serv.	2
22	1	Low	15	3%	reduction bill cost for companies	2
	2	Low	25	<1%	reduction bill cost for companies	2
23	1	Low	15	1–3%	improvement of public work/serv.	2
	2	High	25	1–3%	reduction bill cost for families	2
24	1	Low	20	<1%	improvement of public work/serv.	2
	2	High	20	3%	reduction bill cost for families	2
25	1	High	25	3%	improvement of public work/serv.	1
	2	Low	15	<1%	reduction bill cost for families	1
26	1	High	25	<1%	reduction bill cost for companies	1
	2	Low	15	3%	reduction bill cost for companies	1
27	1	Low	25	1–3%	improvement of public work/serv.	2
	2	High	15	1–3%	reduction bill cost for families	2

Table A2
Socio-demographic information of the sample

Variable	Obs.	Freq.	Percentage	Mean	Std. Dev.
Sex	504				0.50
Male		243	48		
Female		261	52		
Age	504			44.9	13.71
18–25		50	10		
26–35		77	15		
36–50		188	37		

(*continued on next page*)

Table A2 (*continued*)

Variable	Obs.	Freq.	Percentage	Mean	Std. Dev.
51–65		153	30		
>65		36	7		
Area of residence	504				0.67
City centre		260	52		
Suburbs		193	38		
Countryside		51	10		
Education	504				0.82
Elementary/Junior high school		44	9		
High school degree		248	49		
Bachelor degree		150	30		
Post-graduate degree		62	12		
Employment	504				1.41
Housewife		39	8		
Employee		291	58		
Self-employed		63	12		
Student		33	6		
Unemployed		35	7		
Retired		38	7		
Other		5	1		
Monthly expenses	504			1.68	1.00
Up to 300€		295	58		
301-500€		124	25		
501-800€		48	9		
801-1000€		25	5		
>1000€		12	2		

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