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Urban heat mitigation: a theoretical and empirical assessment of economic valuation approaches

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ABSTRACT

Extreme heat in urban areas threatens citizens' well-being, prompting cities to adopt heat mitigation measures. Economic valuation through stated preference (SP) methods provides insights into citizens' willingness to pay (WTP) for such measures, but heat mitigation is a complex, intangible, subjective, and multi-dimensional valuation object. This study contributes both theoretically and empirically by categorizing three approaches to valuing urban heat mitigation: (i) effect-based, valuing the cooling effect itself, (ii) cause-based, valuing the measures causing cooling, and (iii) a hybrid approach integrating both. These approaches offer distinct insights but also present different challenges. Focusing on one important issue, we empirically test how the framing of cooling effects influences WTP using a split-sample discrete choice experiment (DCE) in Vienna with 2,194 respondents. Our results show that when cooling effects were made explicit (via pictograms or a separate attribute), respondents demonstrated higher WTP for greening measures, which could be attributed to increased attribute salience or the positive framing of the effects using visual aids. In turn, it suggests that respondents undervalue heat mitigation when not explicitly highlighted. These findings highlight the importance of explicit communication in SP studies to accurately reflect citizens' preferences and improve the design of effective urban heat mitigation policies.

Key Policy Highlights

- There is strong public support for urban heat mitigation, as reflected in a demonstrated willingness to pay (WTP) of €19 to €50 for various urban greening scenarios.
- The representation of cooling effects in choice experiments significantly shapes citizens' responses and valuation outcomes – WTP estimates are markedly higher when the heat reduction is explicitly and visually depicted.
- Citizens place a distinct and high preference on cooling effects, indicating that such benefits should be clearly communicated when promoting urban greening initiatives.

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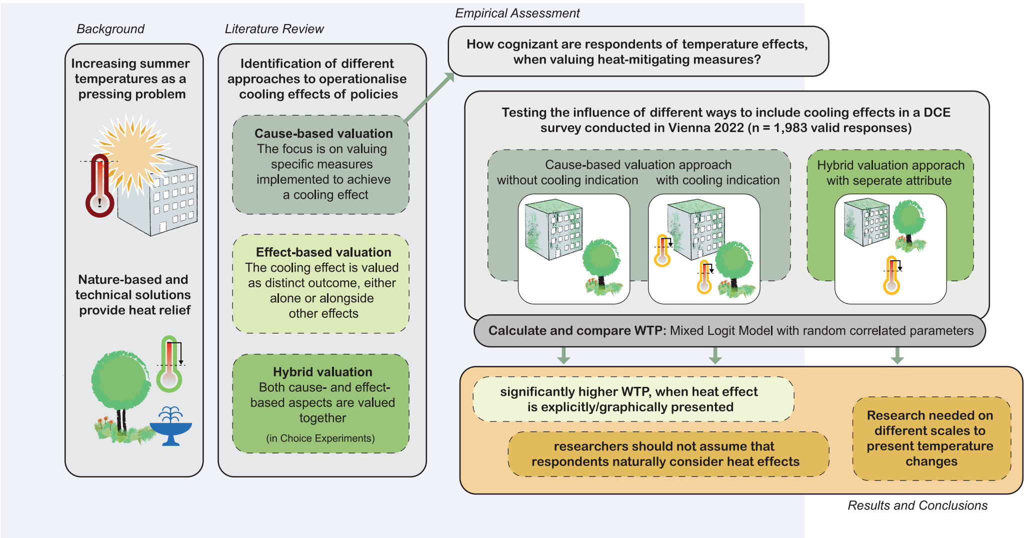

1. Introduction

Heatwaves are among the most dangerous natural hazards constituting a severe threat to human health and lives worldwide (Ebi et al. 2021). Cities are particularly affected due to the urban heat island (UHI) effect. As building materials absorb short and long-wave radiation and transpire heat, airflows are blocked, and anthropogenic heat is released from inhabitants and their appliances, the temperature in densely-build urban areas is significantly higher than in greener neighbourhoods or the surrounding countryside (Founda and Santamouris 2017; Parsaee et al. 2019). For American cities in temperate biomes, a study measured urban-rural temperature differences of 7°C to 9 °C during summer daytime (Imhoff et al. 2010). Increasing urbanisation and the imminent effects of climate change both aggravate the thermal risks for urban residents.

City governments are challenged to implement policies to tackle urban heat and increase outdoor thermal comfort, to adapt to the climate crisis and to improve public health, especially for vulnerable populations. These measures often involve blue infrastructure, like the installation of water elements, as well as green infrastructure, such as the increase of urban greenery, like parks, street trees, green walls or roofs, which are also called nature-based solutions (Wong et al. 2021). Moreover, the application of cooling materials, improving solar reflection or heat storage, as well as the use of evaporative techniques like sprinklers, are commonly used to mitigate the negative effects of urban heat (Qi, Ding, and Lim 2020). As there is no doubt about the need for planning interventions in general, it is interesting to evaluate measures not only in terms of their effectiveness in providing heat mitigation or a cooling effect (which we will use synonymously in this paper), but also in terms of their benefits for different social groups and how they are supported by the public.

The benefit of urban heat mitigation is a public good for which no price information is available, as it is not traded on a market. Economic valuation allows for the monetarization of such non-market benefits (Jain, Kumar, and Paramjit 2015) which is, for instance, a precondition for including them in benefit–cost analysis (OECD 2018). Different valuation methods capture different beneficial aspects of urban heat mitigation. For example, the avoided damage cost approach can be used for health impacts such as avoided premature deaths (Huang et al. 2023) or reduced morbidity and lost productivity measures (Johnson et al. 2021). UHI mitigation can also be valued using a replacement cost approach based on energy savings from cooling (Peng and Jim 2015) or based on its impact on housing prices using hedonic pricing (Kim, Ewing, and Rigolon 2024; Klaiber, Abbott, and Smith 2017).

In addition to these market-based and revealed preference methods, survey-based stated preference (SP) approaches like the Contingent Valuation Method (CVM) and Discrete Choice Experiments (DCE) are widely used to inform stakeholders or policymakers about citizens' WTP and preferences for urban heat management. By presenting hypothetical policies or programmes, these methods provide insights into how people value proposed changes (Hess and Daly 2014). To ensure that these changes are meaningful and interpretable, they should be framed in a way that is 'demand-relevant, policy-relevant, and measurable' and can capture both the underlying cause of a change, such as modifications in an ecosystem, and its resulting effects, such as improvements in air quality (Blamey et al. 2002). While debates on the validity of SP methods persist, past findings suggest that when incentive compatibility (Carson and Groves 2007; Collins and Vossler 2009; Czajkowski et al. 2017; Zawojska and Czajkowski 2017) and consequentiality (Carson, Groves, and List 2014; Vossler and Evans 2009; Zawojska, Bartczak, and Czajkowski 2019) are ensured, the results of SP studies yield valid estimates of actual preferences. SP methods are particularly suitable for valuing public goods (Vossler and Evans 2009) and non-use values (Hanley et al. 1998), both of which apply to changes in thermal comfort, a key objective of urban heat mitigation strategies. However, operationalising urban cooling remains a major challenge, as temperature reduction is an intangible, complex, and multidimensional effect that may not be immediately salient to respondents.

There is a growing public and political awareness of urban heat as a problem and the need for UHI mitigation strategies (Wang et al. 2021). Given this trend, understanding public preferences and WTP for heat mitigation is of high policy relevance, and the number of studies in this field is expected to increase. Despite this, a structured overview of such surveys is so far missing.

This paper addresses this gap by reviewing existing studies valuing urban heat mitigation through CVM or DCE and empirically testing different ways of including heat mitigating benefits into a SP survey. The focus of this paper is to improve the understanding of conceptual and practical challenges of heat mitigation as a valuation object. Accordingly, the following research questions are examined: (1) What approaches were used in the valuation of urban heat mitigation with SP methods? and (2) How does the representation of the cooling effect influence citizens' WTP for heat mitigation?

To answer these questions, the paper consists of two parts. First, it provides a structured review of existing studies on urban heat mitigation, focusing on how the temperature reduction was operationalised in different study contexts. Thereby a distinction is made between effect-based and cause-based valuation as two key strategies for heat mitigation policies, while also noting studies that adopt a mixed approach. Second, it presents an empirical study, a Discrete Choice Experiment conducted in Vienna, Austria. By employing a three-split sample approach, the survey design allows for a direct comparison of different representations of urban cooling effects, providing insights into how respondents perceive and process such information. Thus, this study is also methodologically relevant as it examines how the design of SP surveys, specifically, the way attributes are framed within a DCE, affects WTP estimates (DeLong et al. 2021; Hawley et al. 2008; Veldwijk et al. 2015). In particular, we assess whether framing information or graphical representations of heat attributes are sufficient to ensure that respondents recognize the heat-reducing effects of proposed measures. Thereby, we emphasise the importance of WTP robustness, as variations in attribute representations may enhance attribute salience, which potentially influences the reliability of SP estimates for informing policy decisions (Czajkowski et al. 2016; Fraser et al. 2021; Mattea et al. 2016).

The paper is structured as follows: Chapter 2 reviews and categorises the current state of SP studies on urban heat mitigation. Based on this discussion, a split-sample choice experiment is used to empirically test choice experiment configurations, differencing in the way how the cooling effects are represented. Chapter 3 presents the methodology, including the selection of attributes, the choice and survey design, the sample population, and the estimation approach. The results of the choice experiments are presented in Chapter 4. The discussion in Chapter 5 discusses the empirical findings in light of theoretical considerations and provides recommendations for future SP studies on heat mitigation. Finally, a conclusion is provided in Chapter 6.

2. State of the art: heat operationalisation in economic valuation of heat-reducing urban policies and programmes

With the growing recognition of urban heat as a problem and with more and more cities formulating strategies to combat rising summer temperatures, it is not surprising that the issue is also attracting increasing academic attention. A literature search on the valuation of heat mitigation with SP methods resulted in a total of 17 empirical papers.[1] All studies were conducted relatively recently, with the earliest papers published in 2016. The studies cover different heat mitigation programmes and a wide range of nature-based and technical solutions against urban heat, including different greening measures, cool roofs, and permeable pavements.

Economic valuation of heat mitigation measures and programmes can provide valuable information for urban planning and local governments' decision-making processes about how and to what extent measures should be implemented (e.g. Pearce and Seccombe-Hett 2000; Wilker and Rusche 2014). The city government's demand to better understand the public's awareness, acceptance, preferences and WTP for heat mitigation, is also shown as some of the studies were directly (co-)funded by the local authorities, e.g. in Vienna (Morawetz and Koemle 2017), Prague (Badura et al. 2021), Singapore (Borzino et al. 2020) or Bordeaux (Farina et al. 2024).

Methodologically, the studies can be grouped into those applying contingent valuation and discrete choice experiments. While most of the earliest studies included in the review predominantly used CVM, more recent empirical contributions have largely adopted DCEs. Table 1 gives an overview of the studies, highlighting their research concern and valuation object(s).

2.1. Comparison and discussion of valuation approaches

Based on the reviewed studies, a conceptual distinction can be made between three different approaches to valuing the benefits of urban heat mitigation: (i) effect-based valuation, which focuses on temperature reduction itself, (ii) cause-based valuation, which focuses on specific heat-reducing measures, as well as a (iii) hybrid category, incorporating both causal and effect attributes in the valuation. While these categories are independent of the SP method used, the application of CVM or DCEs allows for different emphases. It must be noted that the most suitable approach always depends on the research context.[2] However, it is still useful to highlight key differences between them, particularly in how they address the subjectivity of heat perception, the ability of respondents to link measures to their temperature effects, and the extent to which valuation studies provide insights into programme design.

2.1.1. Effect-based valuation approach

Effect-based valuation focuses on urban heat reduction as an outcome rather than the specific measures that cause it. Depending on the study design and SP method, heat reduction is assessed as either the single objective of a programme or one of multiple co-benefits.

In effect-based CVM studies, respondents are asked about their WTP for a specific heat mitigation outcome, such as fewer urban heat islands and improved thermal comfort (Borzino et al. 2020) or fewer adverse health effects of heat wave events (Zhang et al. 2016). These studies aim to assess the general public attitude toward urban heat mitigation and interpret WTP as a reflection of public concern. The results provide a single monetary value representing how much respondents value temperature reduction as a policy objective (Bostan et al. 2020), which can be useful for policy design. However, when the valuation is conducted without providing information on the interventions necessary to achieve the outcome, it remains unclear whether citizens would support these specific measures that might involve trade-offs, such as reduced parking spaces or changes in land use.

Table 1. Overview on Valuation Studies.

Authors	Year	City/Cities, Country	Method	Research concern	Valuation object	Heat operationalization valuation type	Description of temperature effect
Badura et al.	2021	Prague, Czech Republic	DCE	WTP for nature-based solutions against climate change effects, including heatwaves	Characteristics of a programme using nature-based solutions (NbS) against urban heat	Cause-based valuation Attributes describe the design of the measures e.g. prevailing type of NbS measure or species composition	Effect of the measures was part of the framing information
Borzino et al.	2020	Singapore, Singapore	CVM	WTP for urban heat island mitigation	Programme to mitigate urban heat effects (80 measures)	Effect-based valuation The valuation question refers to a programme with the effect to improve thermal comfort	Effect described as improved thermal comfort
De Noia et al.	2024* Preprint	Parma, Italy	DCE	WTP for desealing (restoring soil ecosystem services)	Characteristics and benefits of desealing programmes	Hybrid valuation Cause-attributes describe the design of measures, e.g. percentage of desealing area; and effect-attributes the outcomes like post intervention perception of the temperature benefit in summer	Effect qualified as perception of the temperature benefits in summer (strong to weak)
Farina et al.	2024	Bordeaux, France	DCE	WTP for nature-based solutions (infiltration infrastructure and urban greening)	Co-benefits of nature-based solutions (aquifer preservation and local climate regulation)	Effect-based valuation Attributes describe effect of measures e.g. local climate regulation or impact on space for car use, as well as the distribution of the NbS	Effect quantified as a reduction of UHI area in %
Jaung et al.	2020	Singapore, Singapore	DCE	WTP for ecosystem services provided by Singapore's nature	Ecosystem services provided by Singapore's nature	Effect-based valuation Attributes describe effects of measures, referring to ecosystem services, e.g. air pollution or noise reduction	Effect quantified in °C
Johnson and Geisendorf	2022	Berlin, Germany	DCE	WTP for the effects of sustainable urban drainage systems	Ecosystem services provided by sustainable urban drainage systems	Effect-based valuation Attributes describe effects of measures, referring to ecosystem services, e.g. improved biodiversity or water quality	Effect quantified as a reduction of days with more than 30°C
Kim et al.	2016	Seoul, Busan, Incheon, Kwangju, Daejeon, Ulsan, and Daegu, Korea	DCE	Preferences and WTP for life zone forests to mitigate urban heat island effects	Programme to increase life zone forests (street trees, small parks in residential regions, and green areas)	Cause-based valuation Attributes describe design of measures e.g. urban forest area or road size	Effect of the measures was part of the framing information
Morawetz and Koemle	2017	Vienna, Austria	CVM	WTP for two measures against urban heat (trees and drinking fountains)	Programmes to increase trees and/or drinking fountains	Cause-based valuation The valuation question refers to programmes to increase the number or trees and drinking fountains	Effect of the measures was part of the framing information
Nawrath et al.	2024	Chinese cities	DCE	WTP, willingness to contribute time and	Programmes, influencing urban heat, flood regulation, the ecological	Effect-based valuation Attributes describe effects of measures,	Effect quantified in °C

(*Continued*)

Table 1. Continued.

Authors	Year	City/Cities, Country	Method	Research concern	Valuation object	Heat operationalization valuation type	Description of temperature effect
				space for public greenspace management	status of water channels and greenspace management	e.g. flood regulation or naturalness of water channels	
Netusil et al.	2022	Portland, USA	DCE	WTP for different public benefits of green roofs their trade-offs and location	Programme to install 75 additional green roofs	Effect-based valuation Attributes describe effects of measures, e.g. increase in birds, or reduction in sewer overflows, as well as distribution of green roofs	Effect quantified in °F
Rulleau	2024	Strasbourg, France	DCE	WTP for the benefits of sustainable drainage systems	Different stormwater management strategies and their benefits	Hybrid valuation Cause-attributes describe the design of measures, e.g. type of sustainable drainage system; and effect-attributes the outcomes like recreational uses	Effect indirectly quantified using the proportion of green areas and additional pictograms
Salm et al.	2023	Amsterdam, Rotterdam, The Hague, Utrecht, Eindhoven and Groningen, The Netherlands	DCE	Comparison of` WTP and preferences for larger- and smaller-scale urban nature and connected ecosystem services	Characteristics and effects of urban nature projects	Hybrid valuation Cause-attributes describe the design of measures, e.g. urban nature size and type; and effect-attributes the outcomes like air pollution or biodiversity	Effect quantified in °C
Schneider et al.	2024	Vienna, Austria	DCE	Preferences and WTP for urban greening programmes	Urban greening programmes consisting of greening measures in streetscapes and on buildings	Cause-based valuation Attributes describe design of measures e.g. extent of measures on streets or on buildings	Effect described in framing information and indicated graphically on half of the choice cards
Welling et al.	2022	Bremen, Germany	DCE	Preferences and WTP for urban greening programmes	Urban greening programmes consisting of street trees, green areas, and extensive/ intensive green roofs	Cause-based valuation Attributes describe design of measures e.g. extent of measures on streets or green roofs	Effect of the measures was part of the framing information
Zhang et al.	2016	Beijing, China	CVM	WTP for measures against heatwaves	Programme on (1) early warning systems, (2) green and blue infrastructure (3) health consulting, and (4) emergency shelters	Effect-based valuation The valuation question refers to a programme with the effect to reduce heat waves	Effect was described as reducing adverse health effects of heat wave events
Zhang et al.	2019	Beijing, China	CVM	WTP for cool roofs to tackle urban heat island effects	Programme to replace 10% of Beijing's roofs with cool roofs	Cause-based valuation The valuation question refers to a programme to increase the number of cool roofs	Effect of the measure was part of the framing information
Zhang et al.	2021	Guangdong Province, China	CVM	WTP for permeable pavements to tackle urban heat island effects	Programme to replace more than 80% of the urban built-up area with permeable pavement	Cause-based valuation The valuation question refers to a programme to increase the area of permeable pavements	Effect of the measure was part of the framing information

Methods: DCE – Discrete Choice Experiment | CVM – Contingent Valuation Method |||.

Effect-based DCEs allow researchers to estimate a monetary value per unit of temperature reduction, which is particularly useful for cost–benefit analyses. In the studies, the temperature reduction is presented as a distinct attribute of a programme, measured either quantitatively or qualitatively alongside other effects. These studies often refer to various ecosystem services. For example, sustainable urban drainage systems in Berlin and green roofs in Portland not only contribute to heat mitigation but also improve biodiversity and water management (Johnson and Geisendorf 2022; Netusil et al. 2022). However, conceptually, it may not always be meaningful to present different effects as competing attributes when they stem from the same measure. For example, planting a tree will inevitably provide multiple ecosystem services, such as cooling, air purification, and biodiversity enhancement, regardless of how respondents prioritize one benefit over another. Further, an important challenge in this approach is to choose an appropriate scale to ensure that respondents can accurately interpret the temperature effects presented. Thereby, the trade-off between simplicity and realism in the valuation task remains an open question. Presenting cooling effects in qualitative terms may help reduce respondents‘ fatigue and cognitive burden (Meyerhoff and Liebe 2009), but it lacks specificity regarding measurable temperature reductions. Conversely, research shows that humans are generally not able to perceive the single thermal parameter as air temperature, as its perception is strongly related to other factors, such as humidity or wind speed (Andrade, Alcoforado, and Oliveira 2011). Therefore, when the effect of heat mitigating measures is described as a change in temperature, like it is regularly done (e.g. Jaung et al. 2020; Nawrath et al. 2024; Netusil et al. 2022), it is unclear how the respondents interpret the effect on their personal thermal comfort (Morawetz and Koemle 2017). While there are also alternatives operationalising heat mitigation as a reduction of days with a maximum temperature above 30°C (Johnson and Geisendorf 2022) or as a reduction in the area affected by UHIs (Farina, Le Coënt, and Hérivaux 2024), the question of respondents' comprehensibility remains.

2.1.2. Cause-based valuation approach

Cause-based valuation, in contrast, focuses on specific interventions known to reduce urban temperatures, such as urban greening, desealing or green roofs. The heat-reducing effect of the measures is typically described in the framing prior to the SP survey but not directly valued. Instead, respondents are expected to consider the cooling effects implicitly based on the provided information and their personal experiences with the thermal effects of measures such as trees (Morawetz and Koemle 2017, 3).

In cause-based CVM studies, respondents express their WTP for individual urban measures, such as cool roofs or permeable floors (Zhang et al. 2021; Zhang, Fukuda, and Liu 2019). Since respondents value the intervention as a whole, their WTP reflects not only the cooling effect but also co-benefits such as improved aesthetics, air quality, or biodiversity. This introduces a challenge because it remains unclear whether respondents primarily value cooling effects or other benefits. Some studies address this by explicitly highlighting heat-reducing effects in the survey framing (e.g. Zhang et al. 2021) to support that respondents consider heat mitigation when stating their WTP.

The challenge of unclear consideration of the cooling effect also applies to effect-based DCE experiments. Different from CVM, however, their primary focus is to analyse different preferences regarding heat mitigation programmes. Attributes typically describe the type of measure to be implemented, such as green areas versus street trees (Welling, Zawojska, and Sagebiel 2022), the location of the intervention, on buildings versus in streetscapes (Badura et al. 2021; Schneider, Neuhuber, and Zawadzki 2024) or the redistribution of public space, such as converting roads to urban forests (Kim, Ahn, and Kim 2016). These cause-based studies provide actionable policy insights about which measures citizens prefer and how they should be implemented. However, they do not produce a monetary value for temperature reduction itself, making it difficult to isolate the economic benefits of cooling.

2.1.3. Hybrid valuation approach

Lastly, both effect-based and cause-based valuation can be integrated within a single research instrument. For instance, Salm et al. (2023), in their choice cards, present the size and type of urban nature alongside its effects on flood regulation, temperature moderation, and air quality. Similarly, De Noia et al. (2024) incorporate ten attributes, combining the extent and type of desealing interventions with their post-intervention impacts on rainfall and temperatures. Rulleau (2023) also includes various mitigation measures and their effects as attributes. While this hybrid approach may enhance respondents' understanding of the cause–effect relationship in heat mitigation programmes, as assumed, for instance, by Blamey et al. (2002), it also increases survey complexity. This is evident in the relatively high number of attributes, with 7 in Salm et al. (2023) and 10 in De Noia et al. (2024). Furthermore, the challenges associated with distinct effect or cause-based valuations persist, particularly in terms of how to present the cooling effect effectively and clearly differentiate between cause-driven and effect-driven solutions.

3. Research strategy and method

As established, heat mitigation can be examined from different angles, either by focusing on its effects or by assessing the measures that drive cooling. These approaches address distinct research questions, ranging from preferences for ecosystem services and public support for broad heat mitigation programmes to the design of specific policies. Given these differences, directly comparing all approaches would yield little insight as each operates within its own conceptual and methodological framework. However, to advance the discussion, this study centres on a critical question within the cause-based valuation approach by examining the extent to which respondents are cognizant of temperature effects when they are not explicitly mentioned.

Cause-based DCEs hold significant policy relevance as they inform the design of concrete mitigation measures. However, since temperature effects are typically not directly valued but only introduced through survey framing, it remains unclear to what extent respondents account for cooling benefits in their decision-making. Methodologically, survey framing plays a crucial role in SP studies, shaping how respondents interpret attribute levels and navigate trade-offs (Johnston et al. 2017). Moreover, subjective perceptions of urban heat and varying levels of knowledge may affect respondents' ability to link interventions to their cooling effects, highlighting the need to assess how different representations influence understanding and valuation accuracy (Shr et al. 2019).

To address this, the empirical part of this study employs a three split-sample DCE to examine the influence of implicit and explicit representations of temperature effects. The first version follows a pure cause-based design. The second version uses the same design but adds graphical indicators to show the temperature reduction associated with each measure (thus still adhering to a cause-based design, but with a visual reminder of the cooling effect). Finally, the third version follows the hybrid approach by incorporating an explicit cooling effect as a separate attribute within the choice experiment. This approach provides insights into the robustness of WTP estimates and the methodological implications of attribute design in urban climate valuation. The following chapter outlines the attribute selection and representation that is used in the three different choice experiment designs.[3] Further, the survey design and sample population are presented, as are the estimation and comparison approaches. The choice experiments were designed and conducted following the stated preference guidelines by Bateman (2002) and Mariel et al. (2021).

3.1. Attribute selection and choice design

The respondents of the choice experiment were evenly divided into three subsamples. Two of them were presented with only four attributes – a cost and three causal attributes regarding different urban design measures, while the third group received an additional fifth attribute, representing the temperature effect.

There are two greening attributes representing the density of nature-based solutions to be implemented against urban heat. The first attribute (A1) ***measures on streets,*** concerns the plantation of trees and the construction of planters and flowerbeds in streetscapes or in other public places; and the second one described (A2) ***measures on buildings****, i.e.* the installation of green roofs and green facades on public and private buildings. The selection of the attributes according to their place of implementation is inspired by Badura et al.'s (2021) attribute '*Prevailing type of nature-based solutions measures*', differentiating between the implementation of trees and grass-based or building-based measures or a balanced mix. Moreover, it is noteworthy that the aforementioned urban greening measures can be implemented citywide, as they require relatively little space and provide mainly aesthetic and climate-regulating benefits, focusing less on recreational benefits compared to the creation of parks, which allowed the research sample to include all residents of Vienna.

The third attribute (A3), ***street furniture,*** was chosen as an additional attribute, describing non-natural elements, such as benches and fountains. As urban greening initiatives are often connected with a larger redesign of public spaces, this attribute serves as a control variable to distinguish between respondents' preferences for green infrastructure and a preference for a higher quality of stay.

Lastly, each scenario also contained (A5) a ***cost*** attribute of 1–6 euros per month. The design of the cost attribute was based on the literature review and discussed with experts during the pre-testing phase. When setting the lowest level of the cost vector the annual budget of Vienna's Garden and Urban Greening Agency MA42 relating to 13€ per citizen (City of Vienna 2023a) was considered. As payment vehicle, a mandatory contribution to an earmarked fund for heat mitigation was used. Using a binding (nonvoluntary) payment vehicle, as highlighted by Johnston et al. (2017), is important for incentive compatibility and to prevent free riding. The monetary values were also presented as an annual sum (12–72€) as the frequency of the payment was found to have an effect on the WTP (Egan, Corrigan, and Dwyer 2015).

Prior to the choice tasks, all respondents received information on the effects of the urban greening measures, including those on micro-climate regulation, mainly through shading and evapotranspiration. Additional priming on urban heat was also part of the introductory part of the survey, asking respondents questions such as how they perceive heat, whether heat affects their quality of life or sleep, and whether they perceive that summer temperatures are increasing. Respondents were asked about their behaviours to mitigate the negative effects of heat, ranging from using sunshades to installing air conditioning to leaving the city during heat waves. As their preferences for a greener environment could also be influenced by their current use of public spaces, information on the use of green spaces and car ownership was collected. The description of the attributes, framing information and questions of the survey can be found in the supplementary material (Table A). This part of the survey was the same, independent of the type of choice experiment the respondents received. All parts of the survey, including the choice experiment, were intensively discussed in the interdisciplinary project team, and qualitatively and quantitatively pre-tested. During this process, experts in the fields of social and political sciences, as well as spatial planning, were provided with test links to an earlier version of the survey. In total, we received 26 documents with written feedback, which we incorporated to improve the clarity of the questionnaire. Before each round of questioning (in May and September), we pre-launched the survey and checked for inconsistencies in 100 responses. All parts of the three-split sample were equally covered by the pre-testing.

As mentioned before, the sample was split evenly into three groups. The first group's choice experiment consisted of the three causal attributes and the cost attribute previously described. The programme's effect on urban heat was purely stated in the priming. This is consistent with a pure cause-based design, which was, for instance, used by Badura et al. (2021). In the following, this choice experiment is denoted as **4NH** (four-attribute DCE without heat pictogram). The second group received the same choice cards as the first group. The only difference was an additional symbol on the pictogram of measures on streets and measures on buildings, which indicated the cooling effect of the nature-based solutions. This modification introduces an implicit reminder of the effect within the choice tasks, similar to the approach used in cause-based CVM studies (e.g. Zhang et al. 2021). While this version still adheres to the cause-based design framework, it is no longer a pure form. By incorporating visual cues that highlight the urban cooling, it moves closer to a hybrid approach, in which both the cause and the effect are presented. However, unlike the hybrid design, in this version, the effect is not introduced as a separate attribute but only as a visual prompt embedded within the existing attributes. This choice experiment is referred to as **4H** (four-attribute DCE with heat pictogram). Finally, the third group was given choice cards with an additional fifth attribute (A4), ***heat reduction,*** explicitly indicating the scenario's effect on urban temperatures. This DCE follows the hybrid approach, incorporating the cooling effect as a separate attribute within the choice experiment. In the following, this version is referred to as **5H** (5 attribute DCE with heat attribute). To address potential challenges in temperature perception when presented solely in numerical terms, the cooling effect was described both qualitatively either as a 'slight', 'moderate', or 'significant' effect as well as quantitatively by an average temperature reduction of one to four degrees Celsius effective in spatial proximity of the implemented measures. Notably, the lowest level ('none') was assigned only to the status quo, while the remaining three levels were assigned to the remaining alternatives. This decision was made based on the credibility of the choice situation, as increasing the distribution of greening measures (attributes A1 and A2) has a positive impact on the cooling effect (a similar approach was taken up by Farina, Le Coënt, and Hérivaux 2024).

The split sample approach was chosen to test how respondents take urban cooling effects into account when they are presented differently. Assuming that the information about the heat-reducing effects of the measures described in the priming is sufficient to motivate respondents to integrate them into their decision heuristics, thus, if WTP remains robust, there should be no statistically significant difference between these choice experiment designs. Figure 1 shows the different types of attributes and levels used in the three versions of the choice experiment. The abbreviations on the right side of the table indicate in which of the three choice experiments the attribute is used.

The software Ngene was used to find the attribute-level combinations with the highest D-efficiency. While the two four-attribute versions of the DCE used the same choice design, the choice cards of the five-attribute version were composed separately. The experiment design phase resulted in two designs consisting of 24 choice cards each, which were structured in four blocks. Each respondent was confronted with one block of six choice situations in a random order.

3.2. Survey design and sample population

A total of 2,194 Viennese citizens took part in the choice experiments, which were conducted in Vienna in May and September 2022[4], resulting in 1,983 valid responses.[5] The survey was distributed by a market research institute using its online panel of respondents who were compensated for their participation. It was ensured that the selection of respondents was representative of the city's population in terms of gender, education, distribution across Viennese districts and age (restricted to the age groups between 18 and 69). Table 2 shows the sample structure according to the division into the three types of choice experiments. Moreover, it is indicated how the sample relates to the demographic composition in Vienna (City of Vienna 2023b; Statistics Austria 2019; Statistics Austria 2021).

The respondents' socio-economic composition across each type of choice experiment is very similar (as treatment assignment was randomized and Chi-square tests revealed no statistically significant differences between subsamples). Compared to the Viennese population, younger people

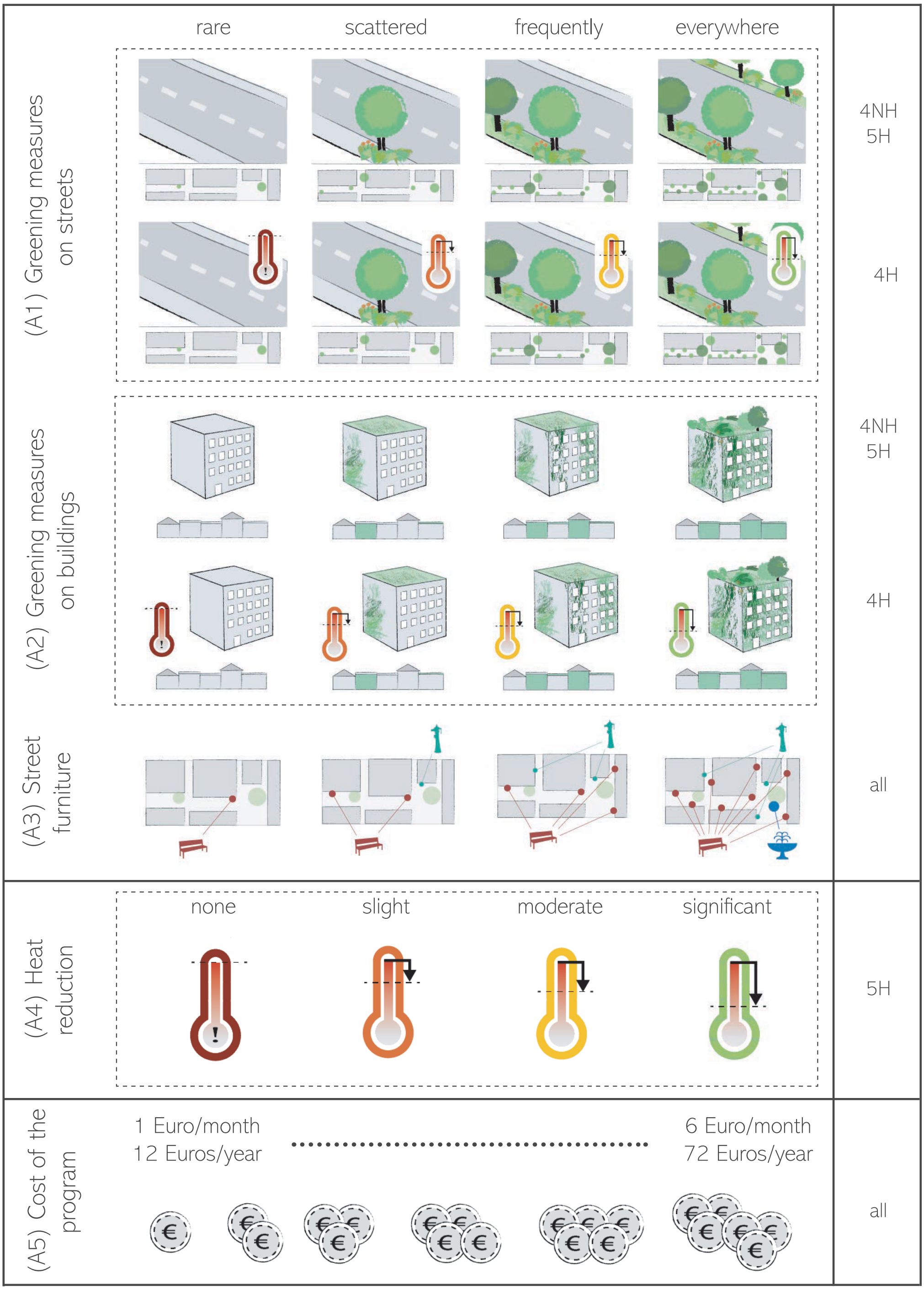

Figure 1. Overview of the depictions of the attribute levels used in the three choice experiment types.

are underrepresented, as no minors were included in the survey. There is also a slightly higher proportion of respondents who finished high school. Nevertheless, the representativeness of the sample can be considered as satisfactory.

Table 2. Sample structure divided by type of the choice experiment and compared with the Viennese population.

Socio-economic variables						
Variables	5H	4NH	4H	Sum	Shares	Vienna
Gender						
Male	319	328	320	967	49%	48.9%[a]
Female	337	336	343	1.016	51%	51.1%[a]
Age						
<30 years	154	142	142	438	22%	34.0%[b]
>30–55 years	324	357	338	1.019	51%	38.2%[b]
>55 years	178	165	183	526	27%	27.8%[b]
Highest Education						
Elementary School, Apprenticeship	304	310	326	940	47%	52.3%[c]
High School	165	166	176	507	26%	19.7%[c]
Tertiary Education	187	188	161	536	27%	27.9%[c]
Monthly net household income						
<2.000€	189	182	208	579	35%	
2.000 - 4.000€	245	233	234	712	43%	
>4.000€	119	130	101	350	21%	

Sources: (a) City of Vienna (2023b) (b) Statistics Austria (2021) (c) Statistics Austria (2019).

3.3. Estimation approach

The foundations of the DCE method are based on Lancaster's Characteristics of Value Theory (1966), which states that the valuation object can be described by its characteristics, which can take on different levels that are varied in each choice task to assess welfare benefits. Moreover, when a cost attribute is included, choice experiments allow the estimation of an individual's marginal WTP for each attribute and thus have the ability to provide more data than could be obtained using CVM (Nakatani, Aramaki, and Hanaki 2007). This makes choice experiments well suited for testing the influence of different methods of presenting urban heat mitigation to be valued by respondents.

Based on the random utility framework (McFadden 1974), the indirect utility function (U) of each respondent (i) consists of two elements. First, there is the deterministic part (V), which is typically a linear function of the observed attributes of the alternative (X_{itj}) multiplied by a vector of parameters (β_i). The second and so-called stochastic part (e_{itj}) is the random error term, which represents all influences on the individual's decisions that are unobserved or unobservable. Assuming that the respondents are following a utility maximising behaviour, an individual i in the choice situation t will choose the alternative j which they associate with the highest personal utility. This can be expressed as:

$$U_{itj} = \boldsymbol{V}_{itj} + e_{itj}$$

In this study, a mixed logit model (MXL) with correlated random parameters is applied (Mariel and Meyerhoff 2018). MXL models extend the simple multinomial logit model (MNL) by including preference heterogeneity. The parameters are thereby not considered as fixed but derived from a statistical distribution. In the present case, the cost attribute was treated as log-normally distributed while all other attributes were assumed to follow a normal distribution. Furthermore, the use of the MXL model is beneficial as it can take into account the panel structure of choices and heteroscedasticity in the error term. In that case, the unconditional choice probability, where the vector of parameters $\boldsymbol{\beta_i}$ follows the distribution $f(\beta_i|\Omega)$, can be expressed as:

$$P_{ijt}(\beta_i|\Omega) = \int_{\beta_i} \left[\frac{\exp(\boldsymbol{X}_{itj}\boldsymbol{\beta}_i)}{\sum_{k=1}^{K} \exp(\boldsymbol{X}_{itk}\boldsymbol{\beta}_i)} f(\beta_i|\Omega) \right] d\beta_n$$

As the integral does not have a closed form a simulation is needed in order to apply log-likelihood maximization. In this analysis, 2,000 Sobol draws (Sobol' 1967) are used, incorporating the scrambling techniques of Owen (Owen 1995) and Faure-Tezuka (Faure and Tezuka 2002) as proposed by Czajkowski and Budziński (2019).

3.4. Comparison approach

To compare the effect of the split sample treatments, interactions (which are the covariates of the random parameter's means) were incorporated into the model. The 5H treatment served as the baseline level, highlighting the differences in preferences for the other treatments (4H and 4NH). Notably, the interactions between heat reduction attributes and 4H and 4NH versions were fixed and constrained to 0, as this attribute was not present in the pure cause-based four-attribute DCE versions. Nonetheless, the differences introduced by adding the additional attribute in the 5H version should become apparent when analysing the alternative-specific constant and related interactions.

To estimate the willingness to pay (WTP), defined as the ratio of all attribute coefficients to the cost coefficient, the Krinsky-Robb method (Krinsky and Robb 1991) was employed. This process involved 10,000 iterations, where in each step, 100,000 random coefficients were generated using a multivariate normal distribution (with a vector of estimated parameters from the MXL model in the preference-space as mean and an asymptotic variance-covariance matrix as a variance). To account for the covariance structure of the random coefficients, Cholesky decomposition was used. For each iteration, the random coefficients were adjusted by constructing a lower triangular variance-covariance matrix, which captured the correlation between coefficients. This matrix was multiplied by random draws from a standard normal distribution and added to the base random coefficients, ensuring that the final parameters followed the desired variability and correlation structure. The WTP was then calculated as the ratio of the adjusted random coefficients. Then, for the 4H and 4NH WTP, interaction terms (covariates of mean) were added to the parameters. Ultimately, this approach enabled us to estimate standard errors and confidence intervals for WTP estimates (Bliemer and Rose 2013; Hole 2007). To compare empirical distributions, the convolution test by Poe, Giraud, and Loomis (2005) was applied, providing a statistical assessment of differences between WTP estimates.

4. Results

Table 3 presents the results of the MXL model with correlated random parameters in the preference space. The first two columns display the mean and standard deviation of the respondents' preferences for the baseline version, 5H (five-attribute DCE with heat attribute), whereas the last two columns show the interactions with the 4H (four-attribute DCE with heat pictogram) and 4NH (four-attribute DCE without heat pictogram) versions.[6] All attributes, except for the cost attribute, were dummy-coded as they do not represent continuous and equal changes between specific levels. For the greening measures on streets (Street), greening measures on buildings (Build), and street furniture (Furniture) attributes, the base level was 'rare', with subsequent levels indicating more extensive distribution ('scattered', 'frequently', and 'everywhere', respectively). Conversely, for the heat reduction (Heat) attribute, the base level was 'slight' heat reduction, with the next two levels indicating a 'moderate' and a 'significant' reduction.

The results highlight general support for the proposed programmes. In the 5H version, which follows the hybrid approach, the attribute regarding heat reduction is the most valued one. Additionally, there are positive significant coefficients for the greening measures, with measures on streets being preferred over those on buildings. Conversely, the street furniture attribute had no significant effect on respondents' decisions, regardless of the level. This pattern is consistent for the causal-based DCEs 4H and 4NH. As a control variable, the street furniture attribute shows that respondents' preferences for urban greening were not driven by their wish for more benches or fountains. Further, the table shows some significant interactions representing

Table 3. Mixed logit model with correlated random parameters in preference space.

	Main effects		Interactions with the means of the random parameters	
	5H base model		4H Interaction (std. error)	4NH Interaction (std. error)
	μ parameter (std. error)	σ parameter (std. error)		
ASC	5.60*** (0.49)	4.45*** (0.34)	−1.67*** (0.50)	−0.91* (0.51)
Street 0→1	1.08*** (0.19)	0.89*** (0.17)	0.44 (0.28)	0.01 (0.28)
Street 0→2	1.81*** (0.23)	2.05*** (0.18)	0.31 (0.29)	0.59** (0.29)
Street 0→3	1.92*** (0.21)	2.08*** (0.15)	0.21 (0.25)	0.93*** (0.25)
Furniture 0→1	0.14 (0.19)	0.93*** (0.23)	−0.35 (0.24)	−0.09 (0.25)
Furniture 0→2	0.07 (0.18)	1.39*** (0.19)	0.07 (0.23)	0.29 (0.24)
Furniture 0→3	0.18 (0.21)	1.70*** (0.18)	−0.12 (0.24)	0.40* (0.24)
Build 0→1	0.34* (0.19)	1.25*** (0.21)	0.72*** (0.26)	0.30 (0.26)
Build 0→2	0.77*** (0.18)	1.70*** (0.25)	0.63** (0.25)	0.76*** (0.25)
Build 0→3	1.24*** (0.18)	1.88*** (0.18)	0.36 (0.23)	0.30 (0.23)
Heat 1→2	1.60*** (0.22)	2.01*** (0.28)	0.00 (fixed)	0.00 (fixed)
Heat 1→3	2.26*** (0.19)	2.30*** (0.21)	0.00 (fixed)	0.00 (fixed)
Annual Cost	−5.08*** (0.35)	2.53*** (0.21)	−0.70** (0.32)	0.12 (0.24)
Model diagnostics				
LL at convergence	−8 146.11			
LL at constant(s) only	−11 717.10			
McFadden's pseudo-R^2	0.30			
Ben-Akiva-Lerman's pseudo-R^2	0.53			
AIC/n	1.39			
BIC/n	1.47			
n (observations)	11 898			
r (respondents)	1 983			
k (parameters)	126			

Notes: All parameters are derived from Normal (μ, σ^2), except for the cost parameter which is derived from Lognormal (μ, σ^2) distribution. While the mean for normal distribution is equal to μ, the mean for log-normal distribution is equal to $exp\left(\mu + \frac{\sigma^2}{2}\right)$. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

differences between the choice experiments. The negative interactions with the alternative-specific constant in the 4NH and 4H versions suggest that without explicitly adding the cooling effect as an attribute, the willingness to choose an alternative over the status quo decreases (though it remains positive). Notably, the 4NH interactions show positive effects for measures on streets (from 'rare' to 'frequently' and 'rare' to 'everywhere') and measures on buildings (from 'rare' to 'frequently'). It is also the only DCE treatment with a significant coefficient for the street furniture attribute, specifically for the change from 'rare' to 'everywhere'. This suggests, that when the cooling effect is only implicitly part of the DCE, the respondents consider other aspects of urban redesign more. The 4H version reveals a significant positive effect for two interactions regarding increasing measures on buildings (from 'rare' to 'scattered' and 'rare' to 'frequently'). More importantly, also a significant negative interaction with the cost attribute can be seen, which indicates that respondents who receive graphical information about heat reduction on the choice cards are less cost sensitive, which has an impact on the WTP values.

Figure 2 shows how the results of the three different choice experiment treatments translate into WTP values.[7] While the mean annual WTP is indicated by the black line, the boxes show the confidence intervals, 2.5% and 97.5%. The significance of the WTP estimates is indicated by the presence or absence of stars above the boxes. No significant WTP values are found for the first level of measures on buildings in the versions 5H and 4NH as well as for most levels of street furniture which indicates that the respondents prioritized greening measures and cooling effects when choosing an alternative. In most cases, a larger change in attribute level also translates into a higher WTP. The exception concerns the WTP for changes from 'rare' to 'frequently' (0→2) regarding the measures on streets in the 4H version and the measures on buildings in the 4NH version, which,

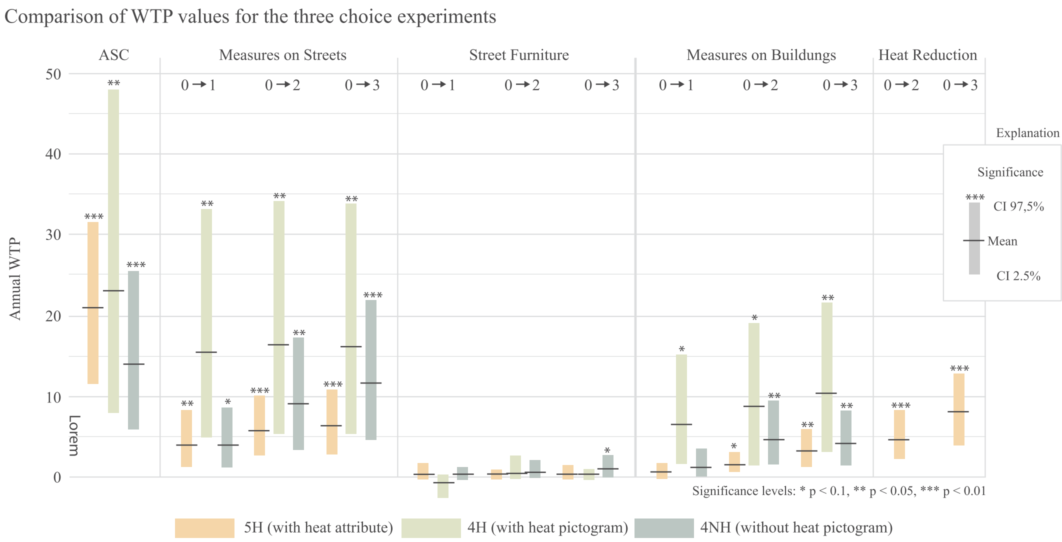

Figure 2. Comparison of WTP values for the three choice experiments.

compared to the WTP for changes from 'rare' to 'everywhere' (0→3), exhibit larger values. Nonetheless, these differences are very small, suggesting that respondents, in some cases, might not differentiate between the 'frequently' and 'everywhere' levels. Further, in the case of the 4H version the respondents seem to be very scale insensitive as they express a high WTP for measures on streets, almost independent of the level.

The WTP values differ across the three DCEs. To further examine the robustness of these estimates, Table 4 presents the results of a one-sided Poe test (Poe, Giraud, and Loomis 2005) (from R's *mded* package). The null hypothesis against which the listed H1s were tested is that there is no significant difference in the WTP distribution between the respective DCEs. While the WTP connected with the alternative-specific constant is similarly high for the 5H and 4H versions, with a mean of 20.97 and 22.91€, respectively, the 4NH version exhibits a much lower mean value (13.90€). However, all alternative specific constants exhibit large confidence intervals and the

Table 4. Results of the Poe test – testing for significant differences in the WTP distribution (H0: No significant difference in WTP between DCE split samples).

	H1:WTP(4H) > WTP (4NH)	H1: WTP(4H) < WTP (4NH)	H1: WTP(4H) > WTP (5H)	H1: WTP(4H) < WTP (5H)	H1: WTP(5H) > WTP (4NH)	H1: WTP(5H) < WTP (4NH)
ASC						
Street 0→1	**		**			
Street 0→2			*			
Street 0→3			*			
Furniture 0→1				*		
Furniture 0→2						
Furniture 0→3		*				
Build 0→1	**		***			
Build 0→2			**			*
Build 0→3	*		**			

Notes: Significane levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
The numbers next to the attributes Street, Furniture and Build indicate the dummy-coded levels representing the extent to which measures are implemented according to the scenarios: 0→1 (change from 'rare' to 'scattered'), 0→2 (change from 'rare' to 'frequently'), and 0→3 (change from 'rare' to 'everywhere'). For the heat attribute, the numbers indicate the level change of the cooling effect: 1→ 2 ('slight' to 'moderate') and 1→ 3 ('slight' to 'significant').
Note that the Poe test is a one-sided test assessing whether some estimates are significantly larger than the others. To address this, we also conducted tests comparing alternative hypotheses to fully capture whether specific WTP estimates differ statistically.

Poe test indicates that the null hypothesis (stating that the WTP distributions are equal) cannot be rejected in these cases. Nonetheless, the differences between the two choice experiments featuring only causal attributes, which vary solely by the presence (4H) or absence (4NH) of the pictogram indicating the temperature effect, are particularly pronounced. Not indicating the heat effect leads to significantly lower WTP values across all attributes. Significant differences are found for the first level of the measures on streets attributes, as well as the first and third level of measures on buildings. In contrast, in the 5H version, where a separate heat reduction attribute is used, respondents' WTP for the cooling effect is also connected with a lower valuation for the greening attributes, especially compared to the 4H treatment (where the Poe test's null hypothesis is rejected for all levels of the greening attributes). While the Poe test suggests that differences between the 5H version and 4NH version are generally not significant, the inclusion of the heat reduction attribute in the 5H version implies a higher combined WTP for this type of DCE, which is further examined in the next part of the result section. Overall, the different results across the DCEs clearly indicate that there is a problem regarding the robustness of WTP values related to the representation of attributes.

The marginal WTP results, detailed in Figure 2 and Table B, can be further combined to form greening programmes of different intensities, as shown in Table 5. The extensive scenario corresponds to an increase in greenery from the 'rare' to the 'scattered' level, the moderate greening scenario stands for a 'rare' to 'frequently' change, while the intensive greening scenario combines the attributes at the level 'rare' to 'everywhere'. In the 5H column, the cooling effect was included in the combined WTP. All non-significant WTPs were excluded from the combined WTP estimates.

Interestingly, the differences in WTP between the levels, representing the extent of greening measures, are small (and mostly not statistically different). This is, on the one hand, due to the high alternative specific constant, which, as the general preference for a change, is constant across all scenarios, and on the other hand, a result of only small differences between the marginal WTP values connected with the levels. Comparing the results for the three choice experiments shows significant differences. The highest WTP values can be found for the choice experiment with four attributes and the additional heat pictogram (4H). The annual WTP is, on average, more than 20€ higher compared to the results of the 4NH version (four-attribute DCE without heat pictogram). The combined WTP for greening scenarios with an additional cooling effect attribute (5H) ranges between the results of the pure causal DCEs 4H and 4NH.

5. Discussion

The non-market nature, intangibility, and subjectivity of heat mitigation make the monetary valuation of policies to reduce urban temperatures complex. This complexity is also reflected in the diverse valuation approaches found in literature. Some studies focus on monetarizing of the cooling effect itself (effect-based valuation, e.g. Bostan et al. 2020; Netusil et al. 2022; Zhang, Fukuda, and Liu 2019), while others assess the measures that are responsible for the cooling effect (cause-based,

Table 5. Comparison of combined mean WTP values for greening scenarios with different intensities.

	5H	4H	4NH
Extensive greening scenario	€ 25.75	€ 44.29	€ 18.98
	(€ 15.28 – € 36.74)	(€ 18.41 – € 79.58)	(€ 8.77 – € 32.07)
Moderate greening scenario	€ 32.78	€ 48.24	€ 27–73
	(€ 19.77 – € 46.25)	(€ 19.46 – € 88.02)	(€ 12.74 – € 46.79)
Intensive greening scenario	€ 38.37	€ 49.68	€ 30.22
	(€ 22.60 – € 54.83)	(€ 20.32 – € 91.16)	(€ 14.12 – € 50.70)

Notes: The extensive scenario corresponds to an increase in greenery from the 'rare' to the 'scattered' level, the moderate greening scenario stands for a 'rare' to 'frequently' change, while the intensive greening scenario combines the attributes at the level 'rare' to 'everywhere'. In the 5H column, the cooling effect was included in the combined WTP for moderate and intensive greening scenarios, accounting for 'moderate' and 'significant' heat reductions.
Confidence intervals (5th and 95th percentiles) are presented in brackets.

e.g. Morawetz and Koemle 2017; Welling, Zawojska, and Sagebiel 2022; Zhang et al. 2021), with some adopting a hybrid approach that integrates elements of both (e.g. Rulleau 2023; Salm et al. 2023). Each method emphasizes different aspects of the analysis and comes with distinct advantages and limitations.

From a policymaker's perspective, valuing heat mitigation measures is especially valuable, as it provides deeper insights into citizen preferences regarding the design and implementation of measures (e.g. Badura et al. 2021). However, for these valuations to be meaningful, it is crucial that respondents understand the connection between the measures and their cooling effects. When heat mitigating measures are valued, the researchers assume that respondents are aware of their heat mitigating effects based on personal experience and/or their ability to process the information provided as part of the framing (e.g. Morawetz and Koemle 2017). The empirical section of this study addresses this issue, examining whether respondents recognize heat mitigation effects when they are not explicitly integrated into the choice experiment design. Specifically, the study tests if making the heat-reducing effects more explicit, by including a heat reduction pictogram in a cause-based valuation or a separate attribute on the choice cards (following the hybrid approach) changes respondents' WTP. If priming and personal experience were sufficient for respondents to account for temperature effects in their decision heuristics, there should be no significant differences between the WTP results of the different treatments.

However, the results clearly show that this is not the case. While the substantial differences in mean WTP values did not always translate into statistically significant differences in empirical WTP distributions, as shown by the Poe test, the treatment variations reveal systematic patterns in how respondents process and integrate cooling information. These between-treatment differences can be attributed to framing effects. Respondents who were graphically reminded of the cooling effect through heat pictograms (4H version) showed less sensitivity to the cost attribute as well as a stronger preference for measures on buildings, and, therefore, exhibited substantially higher WTP than those who did not receive such visual cues (4NH). This pattern might also suggest that, even though all respondents received general information about the link between greening and cooling prior to the choice tasks, misconceptions or limited mental integration of this relationship may still persist and have influenced their choices. Regarding this finding to attribute salience, the extent to which an attribute captures attention and influences decision-making, can play a role (Bordalo, Gennaioli, and Shleifer 2012). It seems that in the 4H treatment, where heat pictograms were presented alongside greening attributes, the measures were more positively perceived, likely because respondents associated them more strongly with their heat-reducing effects. However, respondents in this DCE expressed high WTP values, even for lower levels of urban greening, indicating little scale sensitivity.

In contrast, in the 5H DCE, where heat mitigation was introduced as a separate effect attribute, respondents assigned a distinct WTP to the temperature reduction, while their valuation of greening attributes remained similar to that in 4NH. This suggests that when cooling effects are not explicitly highlighted, respondents primarily value greening itself without strongly associating it with temperature benefits. However, when cooling is presented separately like in the 5H version, respondents clearly recognize and assign additional value to it. The results show that the WTP for the cooling effect itself is even higher than for the greening attributes. Thus, using the hybrid valuation approach, which mixes cause- and effect-based attributes, supports respondents to understand the temperature effect of the measures, which seem to be neglected in the 4NH version. At the same time, it allows researchers to observe directly how respondents allocate WTP to the cooling effect attribute, rather than embedding it within their valuation of the causal greening attributes. Despite the clear advantages of the approach, it remains a path for future research to test which form of describing temperature effect (qualitatively or quantitatively, and on which scale) best supports respondents in terms of enhancing compensability and, ultimately, decision-making quality. In particular, respondents may still struggle to value quantitative temperature reductions expressed in degrees Celsius, highlighting ongoing challenges with scope sensitivity. While this is without doubt methodologically and conceptually challenging, a split-sample design, combined with follow-up comprehension questions, may provide valuable insights into this issue.

While the composed WTP for greening programmes in 5H is higher than the one for 4NH, it is still noticeable lower than for 4NH, indicating that there are still unexplained differences in utility connected with the way the scenarios are presented. This result differs for instance from a comparison between hybrid and non-hybrid DCEs (Blamey et al. 2002), as the researchers found that the reduced WTP for the other attributes offsets the additional WTP for the new attribute. The pattern found in our paper rather indicates that when the cooling benefit is made more salient within an attribute, respondents integrate it into their decision-making differently than when it is framed as a standalone effect. This also opens the question of how other cognitive biases besides attribute salience, may also have influenced these results. For instance, reference dependence might have influenced the responses (Kahneman and Tversky 2013), as respondents' expectations for urban cooling could have been shaped by personal experiences with urban greening in Vienna.

6. Conclusion

As cities worldwide face rising temperatures and increasing heat-related risks, the need for effective urban heat mitigation programmes has become more urgent than ever. Stated preference methods are increasingly applied to assess the value of such measures, yet conceptual and methodological challenges of valuing heat mitigation remain underexplored. This study contributes to addressing these challenges in two key ways: first, by introducing a categorization of different valuation approaches, and second, by empirically testing how the representation of cooling effects influences respondents' willingness to pay for urban heat mitigation.

Our categorization highlights three distinct approaches to valuing urban heat mitigation: (i) effect-based, which values the cooling effect itself; (ii) cause-based, which values measures that cause the cooling effect; and (iii) a hybrid category, which integrates aspects of both. Each method has distinct advantages and limitations. Effect-based valuation provides a direct estimate of the perceived benefits of cooling but may present challenges in conveying temperature changes in a way that respondents can meaningfully interpret. Additionally, it is theoretically possible that respondents, while generally supporting a reduction in summer temperatures, may oppose concrete measures to achieve this result. Cause-based valuation ensures a clear link to policy measures but assumes that respondents intuitively associate these interventions with cooling effects – an assumption that this study directly tested. The hybrid approach improves respondents' understanding of cooling benefits while allowing researchers to separate the valuation of temperature effects from that of greening measures. However, this approach introduces additional complexity in survey design and analysis. Understanding the strengths and trade-offs of these approaches is helpful for designing valuation studies that not only yield reliable estimates but also support evidence-based decision-making in urban climate adaptation policy.

This study's empirical findings suggest that the way cooling effects are represented significantly influences respondents' decision-making. The assumption underlying many cause-based valuation studies, that respondents naturally account for cooling benefits when evaluating greening measures, was not supported by the results of our split-sample discrete choice experiment (DCE). When cooling effects were made explicit, either through a pictogram or a separate attribute, respondents exhibited systematically different willingness to pay (WTP) values. While we anticipated some level of framing effect, the extent to which respondents neglected the temperature benefits in the absence of explicit cues was more pronounced than expected. In the control group, without visual aids or additional attributes, respondents primarily valued urban greening itself without strongly associating it with temperature benefits. Using a pictogram to represent the heat effect of the cooling measures presumably increased the salience of the cooling attribute, leading to higher WTP values for greening measures.

Further, the hybrid approach, using the additional heat reduction attribute, shows the distinct WTP respondents assign to the cooling effect. This also allows researchers to better distinguish between the effects. Altogether, our results suggest that researchers should not assume that respondents will value the cooling effects of interventions to address UHI problems if those effects are not made explicit in the choice cards.

Our findings underscore the critical need for careful consideration of survey design, framing effects, and the presentation of information. Given the role of stated preference methods in guiding government decisions, enhancing the reliability of valuation outcomes is essential to ensure that policy recommendations are derived from robust and well-founded SP studies.

In reflection, our findings open up several opportunities for further investigation. One key question is testing the appropriateness of different scales to present heat-reducing effects in a way that is 'meaningful' to respondents, a challenge for both effect-based and hybrid valuation studies. Additionally, while this study focused on a specific set of measures and a single urban context, there is ample room to explore how these findings can be generalized to other cities with different climates, urban structures, and levels of public awareness.

Finally, our findings also offer insights for policymakers promoting urban greening and heat mitigation programmes. Urban climate impacts are highly relevant to citizens, as demonstrated by their increased willingness to pay when cooling benefits are explicitly integrated into the choice experiment. Based on this, one can recommend clearly communicating the cooling effects in urban planning. Since the public may not automatically associate measures, such as greening programmes, with a temperature reduction, clearly presenting these benefits can improve public understanding, support, and engagement with urban heat mitigation initiatives.

Notes

1. A description of the literature research process can be found in the supplementary materials. The initial literature search identified 13 publications. During the review process, the search was repeated to include newly published studies, adding four more papers to the original sample.
2. This paper does not aim to provide a critical review of the papers analyzed in terms of their research design. Furthermore, this analysis refrains from comparing the results of the studies, as the research questions and contexts are very different, and also the small number of empirically comparable papers does not allow for a quantitative meta-analysis (Alexander 2020).
3. A flowchart outlining the survey process, questionnaire structure, sampling approach, and pretesting is available in the supplementary materials (Figure A).
4. Research on climate mitigation suggests that ambient temperature can be an exogenous driver, with higher temperatures at the time of survey increasing climate change believes (Sugerman, Li, and Johnson 2021) and the WTP for mitigation (Diederich and Goeschl 2014). To test this "ambient heat effect", the survey was conducted in two phases: before and after summer. However, since results showed no significant differences between May and September, no further sample distinction was made.
5. The online panel provider invited 18,901 panelists in May and 27,674 in September 2022 to participate in the survey. The invitation only contained the title of the survey, 'Heat in the City', in order not to provide too much advance information. Although this was done to reduce the risk of selection bias, it cannot be ruled out that respondents may have decided not to participate because of the topic. Of the 3,038 respondents who started the survey, 576 were prevented from finishing the questionnaire due to quota management or screen-outs and additional 272 dropped out voluntarily.
6. To address the issue of differing scale parameters across separate models, an obstacle to direct comparison of DCE treatments (Swait and Louviere 1993), we explored various model specifications. These included approaches that account for scale and coefficient heterogeneity, as recommended by Fiebig et al. (2010), and methods designed to avoid artificially inflating the impact of the additional attribute introduced in the 5H version. Ultimately, however, we opted to estimate a joint model. We believe this approach provides a relatively straightforward yet robust framework for comparing all parameter estimates and assessing the consistency of preferences across experimental treatments, while partially mitigating scale differences. Nonetheless, we acknowledge that not explicitly modelling scale differences might remain a limitation, which we report here for transparency.
7. A table with the WTP values, including standard errors and confidence intervals, can be found in the supplementary online materials (Table B).

Disclosure statement

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