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ARTICLE

Was the trip worth it? Consistency between decision and experienced utility assessments of recreational nature visits

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Abstract

This paper assesses the relationship between decision utility and experienced utility of recreational nature visits. The former is measured as the travel cost to reach that site as routinely used by the travel cost method (TCM), and the latter is operationalized through visit-related subjective well-being (SWB). As such, the analysis is a test of convergent validity by examining whether *ex ante* TCM-based assessment of recreational value reflecting decision utility corresponds to stated *ex post* SWB, reflecting experienced utility. It explores to what extent utility revealed by counts of nature visits are associated with self-reported, visit-related SWB relating to that same visited site. The analysis uses two existing datasets providing information on (i) 3672 recreational visits to green/blue spaces in England over the course of four years and (ii) 5937 recreational visits to bluespace sites across 14 European countries over one year. Results show a positive association between travel cost and visit-related SWB while controlling for trip frequency and a large set of covariates, suggesting convergent validity of the two utility concepts. A breakdown by travel mode suggests this relationship only holds for trips involving motorized transport and is not present for habitual, chore-like walking visits to the recreational site.

KEYWORDS

experienced utility, green/blue spaces, natural environments, revealed preference valuation, subjective wellbeing, travel cost method

JEL CLASSIFICATION
D01, I31, Q26, Q51

1 | INTRODUCTION

Natural environments attract people for recreational visits. This implies that green spaces (e.g. parks, woodlands, heaths) and blue spaces (e.g. rivers, lakes, coasts) generate utility for visitors. An important motivation for the recreational appeal of green and blue spaces may be their positive effects on mental and physical health. A considerable body of research has shown that exposure to the natural environment can be beneficial for people's health and well-being (Bratman et al. 2019; Gascon et al. 2015; Twohig-Bennett & Jones 2018), with emerging evidence suggesting that as little as 120 min a week may be associated with higher life satisfaction and perceived health (White et al. 2019). Nevertheless, the recreational benefits of such natural environments do not typically have a market price by means of which visits can be valued. The travel cost method (TCM) has been used extensively to value many types of recreational sites, including green (e.g. forests, parks and protected areas) and blue spaces (e.g. lakes, rivers and beaches) (Parsons 2017). At its core, the TCM examines the interplay of the cost to reach a recreational site and the number of visits a specific individual makes to that site. The method estimates a demand function for recreation taking travel cost as price. From this demand function, the welfare gain of visiting a site, typically the Marshallian consumer surplus, can be derived (Ward & Beal 2000).

An alternative approach to estimating the utility of a recreational visit to nature is to ask people about their experiences, or visit-related subjective well-being (SWB), either while they are on site (Doherty et al. 2014; MacKerron & Mourato 2013) or shortly after the visit (White et al. 2013; Wyles et al. 2019). The fundamental difference between the two approaches is whether utility assessment is based on observing decisions made about the recreational experience *ex ante*, something Daniel Kahneman refers to as decision utility, or whether it is made based on self-reported introspection during or shortly after an experience *ex post*, which Kahneman refers to as experienced utility (e.g., Kahneman 1994; Kahneman, et al. 1997; Kahneman & Kruger 2006). Clearly, there are potential strengths and weaknesses of both approaches to assessing utility of a nature visit in general (Kahneman & Sugden 2005), but it is reasonable to ask whether they are likely to provide similar or different conclusions or, more generally, whether decision utility is an accurate forecast of experienced utility (Dolan & White 2006). In the context of recreational visits to natural environments, this translates into the question of whether visits that costed more in terms of travel are, ceteris paribus, subsequently associated with higher visit-related SWB. Although this issue has been considered with respect to choice of travel mode (de Vos et al. 2016), we know of no prior study that has considered it in the context of recreational visits to nature.

To explore this research gap, this paper examines the extent to which utility changes induced by green and blue space visits assessed by the TCM coincide with visitors' direct evaluations of such visits based on experienced utility, drawing on two surveys—one in England and the other a pan-European survey. Experienced utility is operationalized here as an index combining self-reported, visit-related SWB following well-established measurement approaches internationally (ONS 2011; OECD 2013). Our measure of visit-related SWB contains four key facets: positive emotions (in this case enjoyment), negative emotions (here anxiety), eudaimonic well-being (here the degree to which respondents thought that the visit was worthwhile), and evaluative well-being (here visit satisfaction). The paper compares utility assessed by the TCM and visit-related SWB by regressing the experienced utility of natural environment visits on individual travel costs, while, importantly, controlling for visit frequency, availability of substitutes and a large number of other personal and site characteristics. So on a methodological level, the analysis in this paper is a test of convergent validity of two concepts of utility by examining whether *ex ante* TCM-based assessment of decision utility of recreational site visits corresponds to stated *ex post* visit-related SWB, reflecting experienced utility.

There is a rich literature presenting comparisons of methods to value environmental goods. Studies have compared TCM and contingent valuation (e.g., Armbrecht 2014; Cameron 1992; Chaudhry & Tewari 2006; Kling 1997; Loomis 2006; Rolfe & Dyack 2010), contingent valuation and the life satisfaction approach (LSA), which relies on statements of SWB as an indicator of experienced utility (del Saz-Salazar et al. 2020; Humphreys et al. 2020) as well as the LSA and hedonic approaches (Luechinger 2009; Ferreira & Moro 2010). The LSA is of particular relevance here because it also draws on people's stated SWB, though in the case of the LSA the focus is on people's overall satisfaction with life rather than the SWB associated with a specific visit to a location. The objective of such research is to explore whether there is convergent validity between the methods in question by testing whether the respective welfare measures for the same change in the provision of an environmental good coincide or are at least correlated (Kling et al. 2012). Although the present study contributes to this literature, it also differs from it because its objective is to explore to what extent revealed preferences for nature visits as assessed by the TCM as an indicator of decision utility are associated with reported SWB relating to that same visit, as a proxy for experienced utility. As such, the present study does not compare changes of welfare measures between methods but simply proxies for different concepts of utility. So on a conceptual level, the study investigates the extent of possible forecasting error with respect to the utility gained from recreational visits to nature and thus adds to another strand of literature, which has been trying to explore the specific utility-theoretic characteristics of SWB data (Benjamin et al. 2021).

The analysis draws on two existing datasets of recreational visits, spanning multiple years and countries, respectively. Information on 3672 visits to green/blue spaces in England between 2014 and 2018 were collected as part of the nationally representative Monitor of Engagement with the Natural Environment Survey (MENE) (Natural England 2019). Within the BlueHealth International Survey (BIS), information on visits to bluespace sites from 5937 respondents across 14 member states of the European Union (Bulgaria, Czechia, Estonia, Finland, France, Germany, Greece, Ireland Italy, the Netherlands, Portugal, Spain, Sweden, UK) between June 2017 and April 2018 was collected (Elliott & White 2020). Although neither dataset was collected as part of a classic on-site travel cost survey, both datasets include dedicated items on recreational visits and associated travel costs, and have previously been used in TCM analyses (Börger et al. 2021; Day 2020).

Results show a positive correlation between travel cost (decision utility) and visit-related SWB (experienced utility) while controlling for trip frequency, income, and a large set of additional covariates, suggesting convergent validity. However, a breakdown by travel mode suggests the relationship only holds for trips that involved some form of motorized transport and is not present for visits where the respondents walked to the recreational site. Further, the relationship between travel cost and visit-related SWB exhibits diminishing marginal effects in both datasets whereby the association becomes weaker as travel cost increases.

The remainder of the paper is structured as follows. Section 2 introduces the TCM and psychological approaches to assessing *ex-post* utility of recreational visits, and justifies their comparison. Section 3 introduces the datasets and methods. Results are presented and discussed in Sections 4 and 5 before Section 6 provides some conclusions.

2 | VALUING RECREATIONAL VISITS TO GREEN AND BLUE SPACE SITES

2.1 | Valuing nature visits ex ante: Travel COST method

The TCM is a revealed preference method, which is based on the assumption that a recreation site is at least worth the amount of money people are willing to spend to visit it in terms of travel expenses and time. The core of the TCM is the estimation of the demand for recreational visits to a site as a function of the cost of such recreation (Parsons 2017). A count data model describes the number of recreational visits to a site y of a respondent as a function, $g(\cdot)$, of travel cost c and a vector $\boldsymbol{X}$ of characteristics of the site and the individual visiting the site:

$$y = g(c, \boldsymbol{X}). \tag{1}$$

Depending on the specific nature of the data collected, there is a range of different count data techniques to estimate the relationship between the expected visit frequency $E[y]$ and c and $\boldsymbol{X}$ (Martínez-Espineira & Amoako-Tuffour 2008). (1) can be derived from the standard utility maximization problem of a consumer choosing between recreation and a range of other goods (Hellerstein & Mendelsohn 1993). This utility maximization problem can also be used to demonstrate why, and under which circumstances, travel cost may be employed as a proxy for decision utility in the travel cost model. According to Hellerstein and Mendelsohn (1993), an individual chooses between the number of site visits y and a vector of quantities of other consumption goods $\boldsymbol{x}$ given the household budget constraint $cy + \boldsymbol{px} = I$. $\boldsymbol{p}$ is a price vector of the other consumption goods and I is income. The utility maximization problem is $\max_{y,\boldsymbol{x}} U = u(y, \boldsymbol{x})\ s.t.\ cy + \boldsymbol{px} = I$, where U is the level of (decision) utility of the recreationist. One of the first-order conditions for a utility maximum is that

$$\frac{\partial u(y, \boldsymbol{x})}{\partial y} = \lambda c \tag{2}$$

where λ is the marginal utility of income. This means that travel cost is proportional to the change in utility from one visit ceteris paribus. In other words, and conditional on constant income and visit frequency, travel cost is a proxy for visit-related *decision utility*.

A rich body of literature has used the TCM to value natural sites, from beaches (e.g. Bell & Leeworthy 1990; Czajkowski et al. 2015; Pascoe 2019: Zhang et al. 2015), woodlands and forests (e.g. Bertram & Larondelle 2017; Englin & Mendelsohn 1991; Willis & Garrod 1991), protected areas (e.g. Martínez-Espineira & Amoako-Tuffour 2008; Navrud & Mugantana 1994), lakes and reservoirs (e.g., Azevedo et al. 2003; Lienhoop & Ansmann 2011) to water activities (e.g., Alberini et al. 2007; Pokki et al. 2018) and other types of recreational visits. With respect to the datasets used in the subsequent analysis, two studies have used these for travel cost analysis. Day (2020) uses the MENE dataset to value the benefits of visiting greenspace in England during the COVID pandemic. This dataset has also been used in the development of the Outdoor Recreation Valuation (ORVal) Tool, which provides monetary values of recreational sites in England (Day & Smith 2016, 2017). Börger et al. (2021) use the BIS dataset to value visits to blue space sites across Europe. Blue spaces are defined as "outdoor environments—either natural or manmade—that prominently feature water and are accessible to humans" (Grellier et al. 2017; p. 3). In addition to a travel cost model as introduced above, this study presents a contingent behavior component to assess the value of varying levels of perceived water quality. Both MENE and BIS datasets are introduced in detail in Section 3.

2.2 | The psychological approach to valuing visits ex-post

A growing literature has been valuing nature visits *ex post* by looking at the psychological effect of visiting natural areas, that is, the mental health and subjective well-being response of visiting nature (e.g., MacKerron & Mourato 2013; White et al. 2013, 2017, 2021; Wyles et al. 2019, Garrett et al. 2019). This refers to an *experienced utility* perspective (Kahneman & Sugden 2005). Compared to the TCM, such indicators of visit satisfaction and enjoyment are (potentially) more direct indicators of the utility impact of a visit. With respect to experiences of nature, people tend to report more positive emotions following such visits than other free-time activities, such as watching television (White & Dolan 2009). Results from two large experience sampling studies that tracked people's emotional states in different locations using smartphone technology found that individuals were happier in natural, especially coastal, environments than urban settings (de Vries et al. 2021; MacKerron & Mourato 2013). Regular visits to nature are also associated with a higher perception of a worthwhile life, and people's ratings of their emotional states "yesterday" are more positive among those who visited nature yesterday, even when this was not made salient (White et al. 2017). Qualitative research also supports the positive role of urban nature in supporting young people's subjective well-being (Birch et al. 2020).

A key advantage of this method compared to approaches based on decision utility, such as the TCM, is that it is not affected by forecasting errors (Wilson & Gilbert 2003). In the case of visits to green and blue spaces, for instance, this error may go in two directions. Individuals may either focus too much on the positive experience of contact with nature, while neglecting in their forecast the negatives that may come with it, such as traffic or overcrowding, or alternatively underestimate the mental benefits from visiting nearby nature (Nisbet & Zelenski 2011). A possible divergence of decision and experienced utility may also result from projection bias, which in turn stems from an underappreciation of adaptation (Loewenstein et al. 2003). There is evidence in many domains that individuals overestimate the pleasure derived from the consumption or an experience because their forecast does not fully account for the degree of adaptation of the experience. So although individuals may correctly predict the direction of a utility change, they may err on the extent. Consequently, individuals may be willing to spend more on a trip *ex ante* than the overall positive *ex post* utility they derive from it would justify.

Other reasons for why a positive association between travel cost and experienced utility may not be found can be highlighted using the utility maximization problem of the recreationist set out in Section 2.1. If expected costs and benefits are too low, individuals may not expend sufficient cognitive effort for the deliberation required for a utility maximizing decision (Welsch & Kühling 2009a). Moreover, as a precondition for the determination of a utility-maximizing decision regarding the number of nature visits, the recreationist requires information on the experience at the site. Individuals for which very few nature visits have been recorded may lack this information and so be more likely to exhibit forecasting error (Welsch & Kühling 2011). Finally, certain visits to nature may not be entirely subject to choice. Walking one's dog for instance may be more akin to an unavoidable chore than a voluntary nature visit. Consequently, for individuals with very few and low-cost nature visits and those who perform a chore-type activity, the expected consistency between decision and experienced utility may not hold.

Nonetheless, critics have questioned whether people's self-reported well-being is a true reflection of their underlying utility given known limitations in people's ability and willingness to reflect on and communicate their emotional and cognitive states (see discussion in Nikolova & Sanfey 2016). Another strand of research into the exact utility theoretic characteristics of self-reported well-being data has found that these statements do not fully overlap with the neoclassical notion of utility (e.g. Benjamin et al. 2021). Despite these concerns there is a very large body of evidence to suggest convergent validity between self-reported well-being measures and physiological indicators, such as neural activity (Sato et al. 2015), ratings of others (Diener et al. 1999), and objective circumstances (Oswald & Wu 2010). Moreover, unlike sensitive topics such as race, there is likely to be far less motivated responding on the relatively neutral topic of nature-based visits (Krumpal 2013), supported by experimental evidence that shows high consistency between physiological and self-report measures of well-being (Park et al. 2010). Last, in a number of countries, there is growing interest in evaluation based on (mainly general) SWB from a policy-making perspective (Frijters & Krekel 2021; HM Treasury 2020; OECD 2018).

A related approach does attempt to assign monetary values to aggregate SWB (i.e. overall life satisfaction) with respect to changes in the provision of environmental goods but is limited for current purposes. Specifically, the LSA (e.g., Welsch & Ferreira 2014; Welsch & Kühling 2009a) is based on the estimation of a well-being function, which describes the relationship among life satisfaction, income, and a set of socio-economic characteristics and other variables that have an impact on well-being (Powdthavee 2008). Drawing upon the relationship between life satisfaction and income, and the resulting marginal rate of substitution between the environmental good and income, it is therefore possible to assign a monetary value to a range of non-market goods such as the availability and access to green spaces (Ruckelshauß 2020; Ambrey & Fleming 2014; Kopmann & Rehdanz 2013), air quality (Ferreira & Moro 2010; Luechinger 2009; Welsch 2006), flooding (Luechinger & Raschky 2009), or the externalities of onshore wind turbines (Krekel & Zerrahn 2017). The LSA is less relevant in the context of specific recreational visits for two reasons. A single nature visit may contribute so little to *overall* life satisfaction that data noise obscures any measurable effect. Secondly, when using visit-related SWB (as in the present study), there is no comparable relationship between income and visit (as opposed to life) satisfaction, and consequently we know of no attempts to place an economic valuation on the SWB associated with specific trips.[1]

2.3 | A comparison of the two approaches

The two proxies for decision and experienced utility can be used to test whether these two utility concepts coincide (Loomes 2006). As explained above, the observation of two respondents making the same number of visits although they incur different travel costs is an indicator of these individuals deriving different levels of (decision) utility from those visits. So our first hypothesis is that visit-related SWB as an indicator of experienced utility should be a function of travel cost for any given number of visits y_i and other controls $\boldsymbol{X_i}$, or

$$\mathrm{SWB}_i \mid y_i, \boldsymbol{X_i} = f(c_i). \tag{3}$$

This reasoning of an expected relationship between travel cost and visit-related SWB conditional on visit frequency allows for a test of convergent validity of the two utility concepts. If decision and expected utility converge for the case of recreational visits to nature, we expect a positive relationship between visit-related SWB and travel cost for a given number of visits, hence:

$$\frac{\partial\left(\mathrm{SWB}_i | y_i, \boldsymbol{X_i}\right)}{\partial c_i} > 0 \tag{4}$$

If decision utility is an appropriate forecast of experienced utility (i.e. visit-related SWB), Equation (4) follows from Equation (2). In particular, we estimate the following regression equation

$$\mathrm{SWB}_i = \gamma_1 c_i + \gamma_2 c_i^2 + \theta y_i + \boldsymbol{\beta}' \boldsymbol{X_i} + \varepsilon_i. \tag{5}$$

where $\boldsymbol{X_i}$ is a vector of respondent and site characteristics including a constant and income, and ε_i is an error term. This specification allows to detect any possible non-linear effect while still nesting the linear model. We prefer this specification because it allows to test whether Equation (4) indeed holds as a linear or non-linear (positive) relationship. In the former case, $\gamma_1 > 0$ and $\gamma_2 = 0$; in the latter case, $\gamma_1 > 0$ and $\gamma_2 < 0$ or $\gamma_2 > 0$. In this last case, visit-related SWB and travel cost co-vary in the sense

[1]Furthermore, there may be serious issues around the endogeneity of any stated indicator of visit or life satisfaction given that the number of recent visits to a site is entirely the choice of the respondent.

that there is a positive correlation. Yet this correlation is not linear but decreases or increases in strength the higher the absolute level of travel cost.

2.4 | Travel mode

Initially, the TCM was conceived by Hotelling in the context of the valuation of national parks (Hotelling 1949), which are specific destinations, ones that people have to make a noticeable effort in terms of time and expense to visit, for example, through the use of a personal car or public transport. So the method was primarily developed to assess the utility of visits associated with reaching a destination via a variety of forms of transport over long distances, initially using a zonal travel cost model (Clawson & Knetsch 1966). In reality, however, most nature visits are close to home and involve walking or cycling to the destination (Wyles et al. 2019; Elliott et al. 2015). There has therefore been an increasing number of TCM applications, which include local recreational trips using a multitude of travel modes (Bertram & Larondelle 2017; Lankia et al. 2019; Tardieu & Tuffery 2019). Although such applications often attempt to value such visits by including the opportunity cost of travel time (routinely by estimating the value of leisure time based on a proportion of income even though this may be unfounded; Czajkowski et al. 2019), it remains unclear how appropriate the TCM is for assessing the utility of the large number of local walking visits, especially if the time taken to reach a site may be utility generating instead of constituting a cost (Abildtrup et al. 2015; Elliott et al. 2015). Consequently, an additional research question is whether any convergence between decision and experienced utility assessments emerges for both visits that involved motorized transport to the site and local (i.e. low-cost) visits where the travel mode was walking. In particular, we test the relationship in (4) for different types of visits. Specifically, we estimate

$$\mathrm{SWB}_i = d_k \gamma_{k1} c_i + d_k \gamma_{k2} c_i^2 + \theta y_i + \boldsymbol{\beta}' \mathbf{X_i} + \varepsilon_i. \tag{6}$$

where d_k is a categorical variable indicating $k = 1, 2, 3$ groups of (i) visits undertaken by motorized, wheeled transport (36.4% in MENE; 67.3% in BIS); (ii) visits done on foot to engage in walking at the site in question (53.2% in MENE; 18.8% in BIS); (iii) other visit types (e.g. with transport mode walking to engage in another activity and generally other transport modes. 10.4% in MENE; 13.9% in BIS).

3 | DATA AND METHODS

This analysis employs two datasets, which are introduced in turn. Subsequently, the main variables are introduced. There are a number of important commonalities and differences in the definition and assessment of both key variables and controls which will be pointed out.

3.1 | The MENE dataset

The Monitor of Engagement with the Natural Environment (MENE) Survey is a cross-sectional online survey commissioned by Natural England, the public body supporting the UK government on environmental matters. The MENE dataset is representative of the English adult population and was collected weekly between March 2009 and February 2020 (Natural England 2019).[2] The dataset includes information on all visits to nature made in the last week, respondent characteristics, including attitudes toward the environment and related behavior, as well as visit-related variables. The

[2]The MENE survey transitioned into the People and Nature Survey in 2020.

latter are elicited for a visit randomly selected from those made in the previous seven days. Information includes the type of natural environment visited, duration of the visit, distance traveled, form of transport used, activities undertaken, motivation behind the visit, impressions of the visit, and incurred expenditures. Information to derive an experienced utility variable (visit satisfaction, visit worthwhileness and visit anxiety) was collected only from year 2014/15 to year 2017/18. Further, we exclude observations with missing information about visit costs, other visit characteristics, and personal characteristics, and also excluded visits carried out on foot with a distance of over 35 miles (56 km), resulting in a sample of $N = 3672$.

The MENE dataset is used with two caveats. First, it does not include visit frequency specifically to the randomly selected site. We attempt to account for this limitation by using as control the overall frequency of visits to nature reported in the past 12 months, which we expect to correlate with visits to the specific greenspace, but recognize potential issues with this approach.[3] Second, the MENE applies only to adults in England, and it is unclear how generalizable any findings are across other geographical and cultural contexts. Both limitations are addressed in the BIS dataset, which we introduce below.

3.2 | The BIS dataset

The BIS dataset is a cross-sectional dataset that was recently collected as part of the H2020 BlueHealth project (Grellier et al. 2017). The international population survey was conducted online in four waves (June 2017, September–October 2017, December 2017–January 2018 and March–April 2018) across 18 countries, but only data from 14 EU member states (at the time of data collection) are used in the present analysis (Bulgaria, Czechia, Estonia, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the UK). Besides questions pertaining to the use of green and blue spaces, mental and physical health conditions, and detailed socio-demographics, respondents were asked a number of questions regarding their last visit to a blue space site, including site type, mode of travel, size of the traveling party, expenditures at the site, and crucially how often in the last four weeks they had visited the site (Elliott & White 2020). Respondents also indicated the location of the site on a map so that road distances between their home and the visit location could be extracted *ex post* (for details see Supplementary Materials in *redacted for blind review*). For the 14 European countries covered, information from 14,745 respondents was collected. Respondents who made no visits to blue spaces in the last four weeks, or for whom different visit information was not available (e.g. round-trip distance to the site), or where visits did not originate from home, were excluded resulting in a dataset for analysis of $N = 5937$. Börger et al. (2021) report the details of how the dataset was cleaned.

3.3 | Outcome variable – visit-related subjective well-being

Both surveys assess the experienced utility of visits to the natural environment through a number of questions. For this analysis, four questions are selected and combined into a single composite index of visit experienced utility (Table 1). For the first three indicators, higher values indicate a more positive visit experience, whereas for the last indicator, these reflect higher anxiety levels. The four questions mirror the four SWB measures, used for example by the UK Office of National Statistics to measure personal well-being (life satisfaction, worthwhile, happiness and anxiety), and reflect, respectively, the evaluative, eudemonic, positive affective, and negative affective well-being

[3]Furthermore, even if previous visit frequency had been collected, recall bias has been suggested to be an issue and respondent may be increasingly vague as to the number of frequently visited sites (Dobbs 1993), which similarly calls into question direct accounts of trip frequencies.

TABLE 1 Survey questions assessing experienced utility indicators

MENE dataset	BIS dataset
Thinking of this visit, how much do you agree or disagree with the following statements?	How much do you agree with the statements below about your visit?
- I was satisfied with the visit	- I was satisfied with the visit
- I found the visit worthwhile	- I found the visit worthwhile
- I enjoyed it	- It made me feel happy
- I felt anxious	- It made me feel anxious

Notes: The variables in the MENE dataset were collected using a 5-point agree/disagree scale whereas those in the BIS survey were assessed using a 7-point agree/disagree response scale.
Frequency distributions are presented in Tables A.1 and A.2 in the Supplementary Materials.

TABLE 2 Response frequency of travel modes in the MENE and BIS datasets

Mode	MENE ($N = 3672$)	BIS ($N = 5937$)
Walking (incl. wheelchair use)	60.91%	29.36%
Car/van/motorcycle	31.21%	57.36% [a]
Train	1.58%	2.03%
Bus or coach	2.26%	4.49%
Bicycle	2.87%	5.59%
Boat (or ferry)	0.01%	0.33%
Other (e.g. horseback)	1.15%	0.83%

[a]The number of UK respondents reporting car/van/motorbikes was 56.35% in the BIS, supporting the notion that the differences in mode percentages across datasets is likely due to the specificity of blue space visits in the BIS, rather than cross-country differences.

component.[4] Following Garrett et al. (2019), the four items were collapsed into an overall visit-related SWB composite as the sum of all response scores with the maximum value scaled up to 100. This was made possible by their strong intercorrelation (Cronbach's alpha for MENE $\alpha = 0.69$; for BIS $\alpha = 0.76$).

3.4 | Travel COST

Our main predictor variable is travel cost, which in both datasets comprises vehicle running costs and the opportunity cost of travel time. Vehicle running costs are specified based on the distance of a roundtrip (to and from visit destination) and on transport mode. Relative frequencies of transport modes for both datasets are displayed in Table 2, with travel by car/van/motorcycle being the most frequent mode in the BIS dataset and walking in the MENE dataset. This reflects the fact that visits to blue spaces (in BIS) are more likely to be at a greater distance from home than visits to the natural environment in general (MENE, Elliott et al. 2015).

To ensure comparability, travel cost is calculated consistently across the two datasets, using the same variables and additional external information (details are in the Supplementary Materials Part B). In addition to travel cost, the MENE dataset includes other visit-related expenditure,[5] which are

[4]In the MENE dataset, visit enjoyment is available for all survey years. Visit satisfaction, worthwhile, and anxiety were instead commissioned by the University of Exeter and collected only for years 2014 to 2018. Visit-related happiness, which is usually used as positive affective indicator in the empirical literature on subjective well-being, was not included in the survey given the similarity with visit enjoyment.

[5]This is based on the question: *"During this visit, did you personally spend any money on any of the items listed on the screen?"* Items include spending on eating and drinking, parking, equipment, items purchased during the visit (such as maps and souvenirs), and admission fees to tourist attractions.

kept separate from the main travel cost variable in the analysis as the latter measures costs per person. The exact reference to the individual or the traveling party is unclear for the related spending variable. Therefore, there may not be a direct association between individual spending and visit experience (for example in case of money spent on food or entry tickets for children or other adults, or in the case of money spent by someone else). The BIS did not include any comparable question.

3.5 | Control variables

In the analysis, we control for a set of visit characteristics, which may explain the stated experienced utility of the visit. These include the type of place visited to differentiate between visits to towns or cities, seaside towns, coastline, and countryside; visit starting point to account for the fact that the psychological experience of visits starting from holiday accommodations may be different than visits starting from home (relevant only for MENE); and activities undertaken during the visit. We further control for the presence of other adults and children during the visit, and time-related variables, like whether the visit was on the day before the interview, whether it took place on a weekend, the season, and the year (relevant only for MENE). The MENE analysis controls for the region of destination, the BIS analysis for country. In terms of respondent characteristics, we control for gender, age group, marital status, presence of disability, working condition, ethnic origin (MENE), income (BIS) or social grade (MENE), region of residence (MENE), and, importantly in both datasets, general SWB. The latter is important to ensure that the effect of experienced utility of the visit is not affected by interpersonal variation of general life satisfaction and therefore represents genuinely visit-related well-being.

Both datasets further include indicators of the perceived availability of alternative recreation sites. In MENE, three attitudinal items were combined into one variable through factor analysis (Supplementary Materials Table A.8) in which higher values reflect higher perceived accessibility/quality. We use factor analysis to build a single indicator capturing the subjective perception of availability of substitute sites. In the BIS, respondents were asked how much blue space was available within a short walking distance from their home ("not sure," "none," "a little," "a lot"); and how satisfied they were with the quality of blue spaces near their home ("very dissatisfied," "dissatisfied," "neutral," "satisfied," "very satisfied," "do not know"). Both variables are included as categorical controls.

Arguably, the most important control variable is the number of visits to the site in question over a specific period. As noted above, no site-specific information on visit frequency is available in the MENE dataset. We therefore use the average number of visits to the natural environment (to any site) in the last 12 months as a proxy for visit frequency to the specific site. The BIS dataset does offer the frequency of visits to the site in question over the 28 days (i.e., four weeks) prior to the interview.[6] This refers specifically to the site for which travel cost was computed and to which the visit-related SWB evaluations refer. With this control in place, travel cost can be interpreted as an indicator of decision utility of the visit, which in turn allows the test of convergent validity presented below.

4 | RESULTS

4.1 | MENE dataset

Table 3 presents descriptive statistics on visit-related SWB, travel costs, and on the main variables included in the models.[7] Visit-related SWB in the analyzed sample ranges from 30 to 100 and is on

[6]Because the BIS was conducted in four seasonal waves, visit frequency did not need to be reported over a whole year to capture seasonal effects. To further preclude that reporting times between seasonal waves overlap the timeframe needed to be shorter than three months. We therefore deem the timeframe of four weeks appropriate to assess visit frequency in the case of this dataset.
[7]See Table A.3 and Table A.4 in the Supplementary Materials for additional statistics on all control variables.

TABLE 3 Descriptive statistics of the MENE dataset

Variable	Mean/share (*N*)	*SD*	Min	Max
Experienced utility: visit-related SWB	85.39	9.38	30.00	100.00
Decision utility: travel cost incl. Time (€)	7.74	11.68	0.17	127.49
Other visit costs (€)	6.17	26.56	0.00	795.45
Nature visits in the last 12 months				
More than once per day	0.128 (469)		0.00	1.00
Every day	0.325 (1192)		0.00	1.00
Several times a week	0.352 (1292)		0.00	1.00
Once a week	0.120 (439)		0.00	1.00
Once or twice a month	0.050 (185)		0.00	1.00
Once every 2–3 months	0.014 (52)		0.00	1.00
Once or twice a year	0.007 (25)		0.00	1.00
Never	0.005 (18)		0.00	1.00

Notes: $N = 3672$. Sampling weights applied. MENE travel cost was not inflation adjusted.

average equal to 85.39. Average round-trip travel costs are €7.74. Other visit costs are equal to zero for 68% of the sample, with a mean value of €7.68. Visits to the natural environment are quite common in the analyzed sample, with 45% of the respondents reporting visits once or more per day, 35% visiting several times per week, and 12% once per week.

Results of Model 1 (Table 4), which pools all trip types, show the existence of a positive association with diminishing effect between travel cost and visit-related SWB.[8] An initially positive relationship between these variables turns negative for travel costs greater than €46.07. Keeping in mind that only in 2.2% of the sample travel costs are above this value, this confirms the positive although diminishing association between decision utility (i.e. travel cost) and experienced utility as operationalized by visit-related SWB (Figure 1).

When interacting travel costs with visit mode variables in Model 2, we find that the positive association between travel cost and visit-related SWB holds only in the case of motorized visits, although only in linear form (with $p = 0.136$ for the quadratic term). The difference in findings between the motorized and walkers groups is robust to (a) a linear model specification for the relationship between visit-related SWB and travel cost, (b) a different model specification, using only the single item visit satisfaction as dependent variable and estimated using ordered logistic regression (Tables D.1 and D.3 the Supplementary Materials).

4.2 | BIS dataset

Table 5 presents descriptive statistics of the BIS dataset.[9] The visit-related SWB indicator has a mean value of 85.41 on a scale going up to 100. Mean travel cost including the opportunity cost of time is €9.72. On average, respondents visited their specific blue space site 4.37 times in the four weeks prior to the survey interview. The minimum travel cost is zero (37 respondents exhibit this travel cost). These are cases for which both the road distance to the site and the travel time extracted was zero. In addition to the results presented below, all models were fitted without these cases, and results are robust.

[8]See Table C.1 in the Supplementary Materials for the full model results.
[9]See Table A.5 and Table A.6 in the Supplementary Materials for additional statistics on all control variables.

TABLE 4 Visit-related subjective wellbeing models including non-linear travel cost (MENE sample)

	MENE Model 1			MENE Model 2		
	Coef.		Std. err.	Coef.		Std. err.
Constant	77.203	***	(2.308)	77.133	***	(2.325)
TC incl. time	0.761	**	(0.367)			
TC^2 incl. time	−0.083	*	(0.050)			
TC (Motorized)				1.064	**	(0.494)
TC^2 (Motorized)				−0.097		(0.065)
TC (Walk to walk)				0.532		(0.480)
TC^2 (Walk to walk)				−0.096		(0.076)
TC (Other)				1.201		(0.739)
TC^2 (Other)				−0.144		(0.092)
TC_max	46.072	***	(12.395)			
TC_max (Motorized)				-		
TC_max (Walk to walk)				-		
TC_max (Other)				-		
N	3672			3672		
R^2	0.173			0.174		
Adj. R^2	0.156			0.157		

Notes: Robust standard errors in parentheses.
Sampling weights applied.
TC_max represent estimates of the turning points of the quadratic functions.
$^*p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

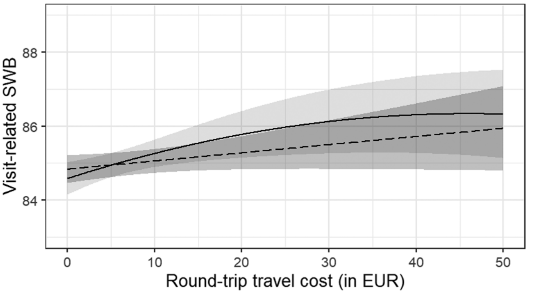

FIGURE 1 Predictions of visit-related subjective well-being as a function of travel cost (MENE dataset) based on the non-linear (Table 4 MENE Model 1, solid line) and linear model (Supp. Mat. Table D.2 MENE Linear 1, dashed line) in green Notes: All other predictors set to their respective sample means. 95% confidence interval bands are plotted in light and dark gray, respectively.

Table 6 displays the estimates of interest of the same set of regression models as used for the MENE data.[10] Note that these models, unlike those based on the MENE dataset, control for frequency of visits to exactly the site in question, as opposed to frequency of visits to nature in general. As for MENE, Model 1 shows that there is a positive relationship between travel cost and visit-related SWB, which loses strength as travel cost increases. The turning point where the coefficient of travel cost turns negative is at €100.82. With 99.3% of all travel cost observations in the sample being smaller than €100, this means that the association between travel cost and visit-related SWB is

[10]The results for the full set of predictor variables can be found in Table C.2, in the Supplementary Materials.

TABLE 5 Descriptive statistics of the BIS dataset

Variable	Mean/share (*N*)	*SD*	Min	Max
Experienced utility: visit-related SWB	85.41	11.94	14.29	100.00
Decision utility: travel cost incl. time (€)	9.72	16.94	0.00	245.41
Visit frequency (in four weeks)	4.37	6.02	1.00	56.00

Notes: $N = 5937$.
Country-specific sampling weights applied.

TABLE 6 Visit-related subjective well-being models including non-linear travel cost (BIS sample)

	BIS Model 1			BIS Model 2		
	Coef.		Std. err.	Coef.		Std. err.
Constant	66.621	***	(4.220)	66.924	***	(4.219)
TC incl. time	0.498	***	(0.168)			
TC^2 incl. time	−0.025	**	(0.011)			
TC (Motorized)				0.470	***	(0.170)
TC^2 (Motorized)				−0.023	**	(0.011)
TC (Walk to walk)				−2.917		(1.843)
TC^2 (Walk to walk)				1.297		(1.194)
TC (Other)				−0.112		(2.099)
TC^2 (Other)				0.237		(1.514)
TC_max	100.815	***	(21.245)			
TC_max (Motorized)				100.303	***	(22.264)
TC_min (Walk to walk)				11.245	**	(5.395)
TC_min (Other)				-		
N	5937			5937		
R^2	0.199			0.200		

Notes: Robust standard errors in parentheses.
Country-specific sampling weights applied.
TC_max and TC_min represent estimates of the turning points of the quadratic functions.
$^{**}p < 0.05$. $^{***}p < 0.01$.

positive throughout but decreasing in strength. In fact, and like in the MENE case, the curvature of this association is so flat that it is empirically indistinguishable from the linear relationship (Figure 2).

A similar picture shows when interactions are used to assess the relationship between travel cost and visit-related SWB for different respondent groups in Model 2. Only for motorized visitors to blue spaces is there a positive though diminishing association between the indicators of decision and experienced utility. The turning point is at a travel cost of €100.03. Notably, the relationship is negative for those respondents who walk to a site to engage in walking-related activities (insignificant in Table 6 but significant in the linear model in Table D.2, Supplementary Materials). The corresponding turning point is at €11.25. Given that 97.9% of respondents in this category have travel costs smaller than this value, this estimated relationship between TC and visit-related SWB is virtually negative throughout.

As robustness checks, we also run these models on two alternative specifications. First, we use a linear specification to model the relationship between visit-related SWB and travel costs (Table D.2 in the Supplementary Materials). This model confirms the significant and positive linear effects for

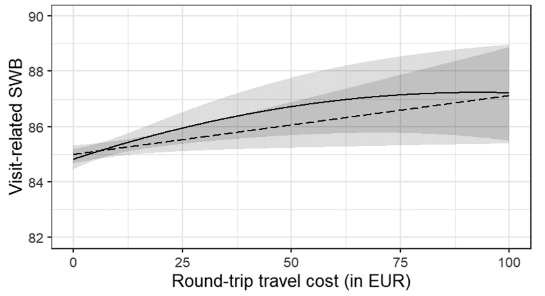

FIGURE 2 Predictions of visit-related subjective well-being as a function of travel cost (BIS dataset) based on the non-linear model (Table 6 BIS Model 1, solid line) and linear model (Supp. Mat. Table D.2 BIS Linear 1, dashed line) Notes: All other predictors set to their respective sample means. 95% confidence interval bands are plotted in light and dark gray, respectively.

the whole sample and the motorized group. The association for the Walk to walk group is negative and significant. For the Other group it is negative but insignificant. Second, we estimate ordinal logistic models on one of the four components of the composite visit-related SWB variable, the ordinal item of visit satisfaction only, which gives the most comprehensive picture of how the visit went, similarly to how life satisfaction is considered the key evaluative indicator of general SWB (Helliwell et al. 2015), (Table D.4). These models support all findings above.

To further explore the negative association between TC and visit-related SWB for those who walk to walk we estimate the above models while distinguishing between those who do the nature visit to walk their dog and those who walk without a dog. It can be argued that walking a dog is more akin to a chore or regular routine, which can be expected to break the positive relationship between TC and visit-related SWB.[11] Looking at results for the BIS dataset (because only here did we find the negative association) we find that the relationship between travel cost and visit-related SWB is in fact positive for those who "walk to walk" when walking with a dog is excluded. On the other hand, a model *only* including those who walked their dog on the nature trip shows a significant and negative linear association between TC and visit-related SWB (full model results in Table D.6 and D.7 in the Supplementary Materials). We interpret these results as evidence suggesting that visiting nature as a chore (i.e. to walk the dog as a routine) undermines the association between TC and visit-related SWB and may even turn its sign.

5 | DISCUSSION

In supporting the hypothesis of converging utility concepts, the results presented above show that the more individuals spend on traveling to green/blue spaces via motorized transport (e.g. private cars, public transport), the higher their subsequent self-reported visit-related subjective well-being. This result holds when only respondents with an equal number of visits are compared. To the extent that our variables are adequate operationalizations of decision and experienced utility, respectively, these results support the notion that individuals are able to make fairly rational *ex ante* assessments of their *ex post* utility and are not prone to substantive forecasting error (Wilson & Gilbert 2003), at least with respect to nature visits. This may be because visits to these precise locations (at least in the BIS) were relatively regular occurrences where the experiences can be predicted with relative accuracy. Yet, additional regression models using respondents who had only made one visit to a blue space in the previous four weeks in the BIS dataset confirm the significant and positive association

[11] We thank two anonymous reviewers for suggesting this exploration.

found in the main analysis (Table D.5 in the Supplementary Materials). So even for non-regular recreational visits, the results support the hypothesis of converging utility concepts. Further, we find the strength of the relationship between experienced utility and travel cost to decline for higher levels of cost. That these patterns are shown (with some variation in strength) across two datasets is testament to the robustness of our findings and is in line with the expectation that the relationship between travel cost and visit-related SWB may be undermined for individuals making fewer trips. Given that there is no easy way to assign values to temporally specific SWB (e.g., that associated with a single nature visit), this should reassure potential skeptics of the TCM (Eberle & Hayden 1991) that the values it generates for such trips are potentially meaningful and can be used for, for example, policy evaluation.

The findings for nature visits that involved walking to and from the site provide insights as to when the convergence hypothesis does not hold. In the MENE dataset the pattern was similar to that for motorized transport, albeit now insignificant. In the BIS dataset, the relationship was negative and insignificant, yet significant in the linear model, with greater travel costs associated with lower visit-related SWB. The finding that the two notions of utility are less aligned for low-cost decisions (i.e., which involve walking) confirms the expectation that individuals are less likely to maximize (decision) utility by carefully weighing up costs and benefits for such a decision (Welsch & Kühling 2009b). Further exploration revealed that the negative relationship between travel cost and visit-related SWB was driven by the habitual, chore-like nature visits of individuals walking their dog. This finding may reflect that such trips are not entirely subject to choice, which undermines the relationship between the two notions of utility.

Nevertheless, given that the only "cost" of walking visits in the TCM is time, this suggests that the longer it took to walk the dog to a blue space, the worse the resulting visit-related SWB was. There is strong evidence of a sharp distance decay for recreational visits to green (e.g. Giles-Corti et al. 2005) and blue spaces (e.g. Elliott et al. 2020), leading various national and international bodies (Natural England 2010) to recommend publicly accessible parks to be made available within a 10–15 min walk, approximately 300–500 m from home (van den Bosch et al. 2016). Local trips are also more likely to be habitual visits, particularly when walking the dog in the neighborhood. When done regularly and in all weathers such trips may be seen as a chore in some instances and associated with lower experienced utility. The implications of habitual behavior, for example, leading to bounded rationality, have been shown in travel route choice (Ramirez et al. 2021), and it is perhaps not surprising that this may apply to decisions around visiting green or blue spaces.

Why this finding only emerged in the 14-country BIS data for blue space visits, and not the in English MENE data for all types of visits, however, is unclear, and such suggestions are clearly speculative at this stage. Further research is needed to explore the underlying reasons for the respective null and negative findings for (habitual) walking visits across our two datasets. Nevertheless, the main conclusion appears to be that the TCM might need to be used with more caution for walking visits, or in studies with a large share of short-distance or walking travel (Bertram & Larondelle 2017; Lankia et al. 2019; Tardieu & Tuffery 2019), than with those involving motorized transport, that is, the context for which it was initially developed (e.g., Azevedo et al. 2003; Bell & Leeworthy 1990; Jeon & Herriges 2010). Advocates of the TCM may question the need to "justify" or cross-validate such utility estimates with an indicator of experienced utility altogether, given the well-documented limitations of these approaches themselves (e.g., Dolan & White 2007). Although understandable, this begs the question why we found such clear and consistent positive relations between travel cost and visit-related SWB for motorized transport, with the kind of diminishing marginal associations. If the findings for motorized transport are accepted by the TCM community, then those for walking visits at least need to be considered further.

What remains less obvious is how to treat the values generated from the TCM for routine walking visits. The SWB approach appears to suggest higher values should be assigned to sites closer to home, supporting calls for better access to local blue spaces for both physical and mental health (Bell et al. 2020; White et al. 2020). Given that these formed the majority of visits to green/blue spaces in the MENE and nearly a third of all blue space visits in the BIS, the potential implications are not trivial (e.g., Bertram & Larondelle 2017; Lankia et al. 2019). Given the novelty of these findings it is perhaps too soon to draw any firm conclusions or make any firm recommendations at this stage. Nevertheless, we would urge TCM practitioners and policy makers interested in utilizing the resulting value estimates to think carefully about the utility of the method for valuing local green and blue spaces.

Despite the confirmation that *ex ante* decision utility and *ex post* experienced utility align for the case of motorized transport, there are a number of conceptual and methodological issues that merit discussion. First, the evaluation of both forms of utility may not exclusively relate to the visit in question. Decision utility as assessed via the TCM refers to more than merely the last visit. In fact, it is likely that their decision (i.e. expected) utility of an option to visit a site may be expressed on the basis of a weighted sum of past experiences. An individual may go to a park she hears good things about or in which she may be interested. The decision for the second visit may then be based both on the past visit and previous experience of similar places. Once the individual visits the n^{th} time, expected or decision utility may be a weighted sum with a stronger focus on the more recent visits. As a consequence, decision utility as operationalized in the TCM may be less prone to forecasting error the more often a respondent has visited the site, an aspect that was suggested with respect to pro-environmental behavior (Welsch & Kühling 2011) and merits further research in this area.

Second, a similar logic applies to the evaluation of experienced utility, which, according to Dolan & White (2006) is an iterative process over time. An individual decides on and experiences an activity, subsequently evaluates it, and decides afterwards whether to engage in it again. Therefore, evaluations of experienced utility, similar to assessments of decision utility by means of the TCM, can be expected to become more accurate with increasing visit frequency. At the same time, the risk of measurement error increases as well because a respondent may (consciously or unconsciously) confuse the experience of different visits even when being asked about a specific (recent) visit.

Third, due to the fact that both datasets are cross-sectional, concerns about potential endogeneity of travel cost with respect to visit-related SWB may exist. For instance, it is conceivable that, as an example of reverse causality, respondents who enjoy their nature visit a lot may extend the stay and thus increase travel costs. However, we deem the chances of reverse causality to be rather slim because given how travel costs are computed in the two datasets (i.e. transport mode-specific road and time costs of the way to the site and back) they can hardly be influenced by decisions after the decision about the trip as such has been made. Moreover, to reduce the probability of omitted variable bias the analysis controls for a large number of covariates even if such bias cannot definitely be ruled out.

Fourth, a caveat of our findings in support of the hypothesis of convergent utility concepts may be that an alternative explanation of the positive association between TC and visit-related SWB is that respondents say they enjoy more expensive visits more in an attempt to rationalize high costs *ex post*. For the case of different types of pro-environmental behavior Schmitt et al. (2018) found that perceived satisfaction with such behavior increases in its costs. Such a mechanism is conceivable for recreational visits to nature as well and would therefore be an alternative driver of the link between TC and visit-related SWB. A related, but distinct, point is that individuals may try to rationalize high travel costs by convincing themselves they experienced more positive emotions and reflections than they really did. The two datasets at hand do not allow for an analysis into these alternative motives so we leave this question for future research.

6 | CONCLUSIONS

This paper presents an analysis of the relationship between *ex ante* decision utility and *ex post* experienced utility of recreational nature visits. The two concepts are operationalized using travel cost to green and blue space sites, and visit-related SWB related to a specific recreational visit. Results based on two large-scale datasets with differing spatial and temporal coverage suggest that, conditional on controlling for visit frequency, travel costs are related to measures of experience utility. This positive association exhibits a diminishing marginal effect and thus weakens with increasing travel cost. However, this association is found only in the case of visits carried out using motorized transport, whereas the costs of walking as a travel mode do not predict experienced utility. This suggests the need for caution in using the TCM to value recreational visit to natural environments in the case of short-distance, casual walking visits. Moreover, as in this case travel costs are represented by the cost of travel time only, this stresses the importance of exploring different strategies to evaluate the opportunity cost of time (Czajkowski et al. 2019). Although the present study represents a first attempt to explore whether utility assessments of recreational visits by means of the TCM coincide with scores of experienced utility gained through visits to green spaces, this approach leaves open a number of questions and thereby suggests avenues for further research. This relates to recent suggestions in the field of recreation demand analysis for the use of perceived site quality in a trip generation function (i.e. to determine decision utility) while at the same time relate objective measures of site conditions to statements of experienced utility (Lupi et al. 2020). For such a comparison to work, the analyst needs to have information on the relationship between decision and experienced utility regarding recreational nature visits. In particular, and based on the findings of this analysis, we recommend including items to elicit experienced utility in TCM surveys. Such data will allow further investigation of the potential alignment (or lack thereof) of these two concepts under specific conditions.

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SUPPORTING INFORMATION

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