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Public preferences for skin cancer prevention policies: a discrete choice experiment in three European countries

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ABSTRACT

Objective: In many countries, the incidence of skin cancer is growing rapidly, resulting in a substantive health and economic burden. While the wide range of available skin cancer prevention policies may have large individual and societal benefits, many countries still lack a policy strategy, and little is known about public preferences for collective prevention policy measures. We elicited these preferences using a discrete choice experiment (DCE) in Austria, the Netherlands, and Spain to inform policy action.

Methods: Respondents were asked to choose twelve times between two packages of different prevention policies. Each package was described by its estimated effectiveness and costs. Before and after the DCE, respondents were asked for their support for any policy action. We quota-sampled adult citizens in each of the countries from an online panel (N = 2,442). The choice data were analyzed using multinomial logit (MNL) and mixed multinomial logit (MMNL) models.

Results: Almost all attributes significantly influenced respondents' choices, with the tax attribute being most influential in each country. Among the six policy measures, information campaigns and a price reduction of sunscreen were the most preferred policy measures, and the prohibition of solar bed sales and solaria the least preferred. Preference structures were largely consistent across the countries. Finally, most respondents supported policy action, particularly after the DCE.

Conclusions: Citizens in the three countries recommended their governments to take policy action against the increasing incidence of skin cancer. The results provide policymakers with directions for publicly supported policy action, which should be complemented with additional information on preference heterogeneity, citizens' argumentation, and policies' relative (cost-)effectiveness. The suggestion that preferences for policy action adapted over the course of completing the DCE survey should be further examined.

1. Introduction

In many countries, the incidence of skin cancer is high relative to other cancer types and, moreover, increasing rapidly (Hu et al., 2022; Leiter et al., 2020). For instance, skin cancer accounts for approximately a third of all cancer diagnoses worldwide (Roky et al., 2025). The global age-standardized incidence rate of non-melanoma skin cancer was estimated to have increased by about 46 % between 1990 and 2019, and its number of new cases and deaths is predicted to grow by at least another 50 % between 2020 and 2044 (Hu et al., 2022). As such, some experts speak of a skin cancer epidemic (e.g., Asadi et al., 2023; Urban et al., 2020), which is supposedly caused by a combination of demographic developments (i.e., population ageing), ecological factors (e.g., ozone layer depletion, global warming), and behavioural trends (e.g., changes in clothing style and beauty norms) (e.g., Asadi et al., 2023; Chang et al., 2014; Watson et al., 2024).

The growing incidence of skin cancer is associated with increasing healthcare expenditures (e.g., Guy et al., 2015; Meertens et al., 2024; Noels et al., 2020). The global economic burden of skin cancer was estimated to amount to $715 billion international dollars (i.e., $80.90 international dollars per capita or 0.015 % of total GDP) in the period 2020–2050 (Chen et al., 2023). It is estimated that the vast majority of

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skin cancer cases (around 90 %) is attributable to excess ultraviolet radiation (UVR) exposure and, as such, preventable (e.g., Leiter et al., 2020; Teng et al., 2021; Yu et al., 2024). Therefore, the gains of prevention policies are likely substantial (e.g., Collins et al., 2024; Gordon and Rowell, 2015; Køster et al., 2020) and include an improved population health and wellbeing and reduced (functional) morbidity, increased labour force productivity, and healthcare expenditure savings.

Therefore, investing in skin cancer prevention is paramount from a public health and economic perspective. A range of policy alternatives is available, including awareness campaigns, prohibition of solar beds or solar studios, screening programs, and free provision or price regulation of sunscreen, all varying in their effectiveness, costs, and restriction of individual freedoms. It remains unclear, though, which prevention policies are preferred by the public. A few studies have elicited user preferences for individual prevention methods such as sunscreen (Solky et al., 2007), screening programs (Houston et al., 2016), and mobile screening applications (Gaube et al., 2024; Haggenmüller et al., 2021; Sangers et al., 2021). However, no studies have elicited citizens' preferences for collective action.

It is important that citizens' preferences are incorporated in the policy development and implementation process for several reasons. This contributes to the legitimacy of policy interventions, which is important in democratic societies. Citizen involvement may also help policymakers in enacting specific policies and adapting their communication to different population segments. Finally, societal support is desirable for an effective implementation of health policies, as it contributes to adherence (e.g., Gustavsson and Lindblom, 2025; Salloum et al., 2017).

Therefore, this study aims to elicit preferences from a representative sample of the general population for various skin cancer prevention policies using a discrete choice experiment (DCE) in three countries: Austria, the Netherlands, and Spain. Using EU-wide data from the European Cancer Information System (ECIS) (European Commission, 2023) on the incidence of melanoma, the most severe type of skin cancer, we selected one EU country with a relatively high incidence (the Netherlands), one with a relatively low incidence (Spain), and one around the EU average (Austria). The aim of this study is to provide insight into between-country similarities and differences in public preferences for skin cancer prevention policies, not to explain them.

2. Methodology

2.1. Set-up of the DCE

We used DCE as the stated preference elicitation method for its ability to capture the trade-offs that respondents make between different policy measures and their characteristics and effects. As such, the method has been widely applied in the health domain (e.g., Soekhai et al., 2019). One of the potential uses of DCE is the elicitation of citizens' preferences towards health policies, such as preventive interventions. DCE applications with this purpose have, for example, elicited citizens' preferences for policies promoting a healthy diet (Dieteren et al., 2023), reducing and preventing obesity (Lancsar et al., 2022), stimulating the uptake of a COVID-19 vaccine (Mouter et al., 2022), and limiting the consumption of alcohol (Pechey et al., 2014).

An important step in the conduct of a DCE is the selection of policy alternatives, attributes and levels. This selection is based on a review of the scientific literature and existing practices of skin cancer prevention, expert consultation, think-aloud pre-testing, and pilot studies and is described in more detail in Supplementary Material 2. The six selected policy measures (see Table 1) are included as dichotomous attributes (Yes/No) in the choice tasks, so that each alternative in a choice task is a policy package consisting of one or more policy measures.

The policy packages differed in the policies they contain and in their estimated effects. Three effect attributes were included in the DCE, capturing the impact of a policy package on the (1) yearly number of new cases of skin cancer, (2) the yearly number of deaths due to skin cancer, and (3) a tax increase. Since skin cancer typically develops over a long period of accumulating excess exposure to UVR, the policy packages are expected to affect the number of new cases and deaths only in twenty years. On the contrary, the tax increase is effective immediately; the policy packages namely require public investments upon their implementation (and enforcement), while the revenues in the form of averted healthcare expenditures or increased workforce productivity are uncertain and expected to be realized in the long run. The levels for all three effect attributes are presented textually as well as graphically (using bars) to enhance respondents' understanding of the attribute levels. An overview of all attributes and levels is presented in Table 1.

All in all, each choice task included two policy packages described by nine attributes. In each choice task, respondents were asked to choose one of the two policy packages. We opted for a forced choice (i.e., not offering an opt-out or status quo alternative) to elicit respondents' trade-offs, given that the question to respondents was which policies to prevent skin cancer they preferred the government to implement, not whether they preferred policies to be implemented. We asked respondents whether they would recommend the government to implement any (additional) skin cancer policies separately, both before and after the DCE.[1] At the top of each choice task screen, respondents were informed about the estimated number of new skin cancer cases and deaths per year in twenty years under the status quo (i.e., when no policy package is implemented). In case of level overlap (i.e., both policy packages containing the same level for a specific attribute), the

Table 1
Overview of attributes and levels in the DCE.

Attribute	Levels			
	1	2	3	4
Policy measures				
Information campaigns	No	Yes		
Prohibition of the sale of solar beds for home use	No	Yes		
Prohibition of solar studios	No	Yes		
30 % reduction of the price of sunscreen	No	Yes		
Free provision of sunscreen in public areas	No	Yes		
Free provision of an app for skin cancer detection	No	Yes		
Effects of the measures				
Number of new cases per year[1]	−5 %	−10 %	−15 %	−20 %
Number of deaths per year[1,]	−10 %	−15 %	−20 %	−25 %
Costs (tax increase)[2]	€36 per year (€3 per month)	€72 per year (€6 per month)	€108 per year (€9 per month)	€144 per year (€12 per month)

Notes: 1) For each country, a status quo in twenty years from now in the absence of any measure was determined (see Supplementary Material 2) and the percentages were therefore expressed in absolute numbers that differed between countries. 2) The costs in this table were presented in Austria and the Netherlands, which had similar price levels, and were adjusted to match the price level in Spain using OECD data (OECD, 2023), so that respondents in Spain were presented with prices between €30 - €120 per year.

[1] The question presented before the DCE was: 'Would you recommend the government to take any policy measures to protect people against skin cancer?'. The question presented after the DCE was: 'Now that you have made a choice between policy packages twelve times, would you recommend the government to take any policy measures to protect people against skin cancer?'.

Fig. 1. Example of a DCE choice task (translated to English).

background of the levels was coloured in grey to simplify the comparison of policy packages for respondents (e.g., Jonker et al., 2018; Norman et al., 2016). To mitigate attribute ordering effects (Boxebeld, 2024), the order of the six policy measure attributes was randomized between respondents, while the order of the three effect attributes was fixed for all respondents, considering that presenting both effectiveness attributes first and the tax attribute next would be a more natural grouping of these attributes for respondents than presenting them in an entirely random order, and given limitations of the survey software. Similarly, the left-right position of the policy package in the choice task was randomized and an alternative-specific constant (ASC) was included in the choice models to capture any alternative ordering effects (Boxebeld, 2024). An example of a choice task is presented in Fig. 1.

Apart from an introduction and the DCE choice tasks, the survey contained several additional questions: prior to the choice tasks, respondents were asked for their age, gender and educational attainment (as screening questions for the quota sampling) and after the choice tasks, they were asked to motivate their choices using open-ended questions. The survey instrument, including the DCE, was programmed in Sawtooth Lighthouse Studio v.9.14.2 (Sawtooth Software, n.d.).

2.2. Experimental design

For the pilot studies, an efficient design was generated using Ngene v.1.2.1 (ChoiceMetrics, n.d.). The priors for the policy measure attributes were set at zero. The attributes regarding the effects of the policy measures were all dummy-coded. For reductions of 5 %, 10 %, 15 %, and 20 % in the number of new cases of skin cancer per year, the priors were set at 0.1, 0.2, 0.3 and 0.4, respectively. The same priors were used for a 10 %, 15 %, 20 % or 25 % reduction in the number of deaths due to skin cancer per year. Finally, the priors for the cost attribute were specified at −0.1, −0.2, −0.3 and −0.4 for a tax increase of €36, €72, €108, or €144 per year (i.e., €3, €6, €9, or €12 per month) (for AT and NL, or equivalent levels in ES). The coefficients resulting from the estimation of an MNL model on the pilot data in the Netherlands ($N = 151$) were used as inputs for Bayesian priors in the generation of the final design for all three countries to eliminate between-country variation in results due to experimental design differences. The pilots in Austria ($N = 102$) and Spain ($N = 101$) were only used to check whether respondents correctly understood the survey. The final design was optimized for the Bayesian D-criterion for an MNL model (without interactions) using 1,000 Sobol draws. Two restrictions on possible combinations of attribute levels were imposed (see Supplementary Material 3) and 36 choice tasks were generated and grouped into three blocks. Respondents were randomly assigned to one of the three blocks of 12 choice tasks each. To minimize any bias from choice task ordering effects (Boxebeld, 2024), we randomized the order of choice tasks in the DCE sequence between respondents. Also, we presented respondents with two instructional choice sets (with fixed levels) to gradually build up the choice task complexity and disclosed the attribute level ranges and number of choice tasks in advance.

2.3. Data collection

The data were collected in the three countries from online panels administered by Dynata (Dynata, 2022), a worldwide-operating provider of survey services. Panel members were quota-sampled by the panel provider with the aim of obtaining samples representative for the country's adult population in terms of age, gender, and education level. Data collection took place between November 21 and December 11, 2023. Given the size of the choice task, survey access was restricted to computers only. To exclude low-quality response patterns, a few data exclusion criteria were used (see Supplementary Material 4). After exclusion of 50 respondents (i.e., 2.0 % of the initial sample),[2] a sample of 2,442 respondents remained for the analysis. The country-specific subsamples are described in terms of sociodemographic characteristics in Table S1 in Supplementary Material 1.

2.4. Model specification and estimation

The DCE data were analyzed for the three countries separately using a Multinomial Logit (MNL) model. Under this model, embedded in Random Utility Theory, the utility derived from an alternative can be divided into a deterministic component and a stochastic component. The deterministic component consists of the sum of the utilities derived from the attribute levels of the alternative, while the stochastic component is captured in an error term.

When comparing the three countries, there may be heterogeneity in preferences as well as in scale, because of which the beta coefficients cannot be compared directly. Therefore, relative measures were derived from the estimated choice models, as these relative measures can be compared between countries. For the MNL models, relative attribute importance was measured using both attribute-based normalization and profile-based normalization (Gonzalez, 2019). The effect attributes in the first estimated MNL models were dummy-coded, like in the experimental design, to check for linearity of the parameters. Based on the MNL estimates, we applied an attribute-based normalization. For each of the attributes, the greatest attribute importance (i.e., the difference in utility between the most and least preferred attribute level in a country) was derived. Next, the importance of the attribute with the greatest difference in utility between the most and least preferred attribute level was normalized to 1, and the importance of the other attributes was expressed relative to the tax attribute. Notably, in the attribute-based normalization, it is assumed that the importance of the attribute with the greatest importance is equal between countries, which may not be the case. Therefore, we also applied a profile-based normalization, for which the total difference in utility between the (theoretically) most and least preferred policy package was calculated (Gonzalez, 2019).

In addition, to accommodate random heterogeneity in preferences, Mixed Multinomial Logit Models (MMNL) were estimated. We allowed for random heterogeneity in all attributes, including the ASC, to avoid the misattribution of heterogeneity. MMNL models are continuous mixture models, in which the choice probabilities do not come with a closed-form solution. Therefore, the choice probabilities were approximated using simulation based on 5,000 Sobol draws. The panel structure of the data was accounted for, so that random preference heterogeneity is allowed for between respondents, but not within respondents. Given that the coefficients of the dummy-coded tax attribute in the initial MNL models showed a reasonable degree of linearity (see Table 2), the tax attribute is treated continuously in the MMNL models. This facilitates the calculation of welfare estimates and unifies the estimated choice models with economic theory (Mariel et al., 2021). The coefficients of the two dummy-coded effectiveness attributes in Table 2 show a lack of linearity. To account for this non-linearity while simultaneously allowing these two variables to be included in a continuous fashion, which facilitates model convergence, these were Box-Cox transformed (e.g., Tuhkanen et al., 2016). The resulting utility function of the MMNL model takes the form:

$$U_{itj} = ASC_j + \beta'_i X'_{itj} + \frac{\delta'_i {N'_{itj}}^{\lambda} - 1}{\lambda} + \rho_i tax_{itj} + e_{itj}$$

in which U_{itj} represents the utility that a respondent i derives from choosing alternative j in choice task t, ASC_j is an alternative-specific constant estimated for one of the two alternatives in a choice task to capture any alternative ordering effects (Boxebeld, 2024), and e_{itj} is a stochastic error term. Furthermore, X'_{itj} is a vector of the policy-specific attributes that characterize alternative j, and β'_i is a vector of taste coefficients corresponding to the policy-specific attributes. N'_{itj} is a vector of the two effectiveness attributes (i.e., number of new skin cancer cases; number of skin cancer deaths), δ'_i is a vector of taste coefficients corresponding to the effectiveness attributes, and λ is the non-linear transformation parameter to be estimated. Finally, tax_{itj} is the tax attribute level of j and ρ_i is the taste coefficient for the tax attribute.

To interpret and compare the MMNL estimates across countries, we computed the marginal rate of substitution (MRS) between each of the policy-specific and effectiveness attributes and the tax increase attribute. We take the (negative) ratio of the unconditional distributions for both parameters, which takes the following form for the policy-specific attributes:

$$MRS_i = -\frac{\beta_i}{p_i}$$

The standard errors have been computed using the Delta method (Bliemer and Rose, 2013). Since the effectiveness attributes are included non-linearly in the MMNL models, the MRS distribution between these attributes and the tax attribute is not constant either but varying by the level of the effectiveness attribute. To obtain the MRSs for these attributes, we worked out the partial derivates of the utility function including the estimated transformation parameter λ and the unconditional distribution of the δ for the attribute in question, with respect to the attribute levels included in the DCE. Then, the ratio was taken between the resulting distribution and the unconditional distribution for the tax attribute parameter, yielding a MRS distribution that is specific to a particular value of the attribute:

$$MRS_{N,i} = -\frac{\delta_i N^{\lambda-1}}{p_i}$$

The distribution of the random parameters is specified as normal for the ASC_i and β_i parameters:

$$\beta_i = \mu + \sigma\zeta_i$$

in which μ and σ are the mean and standard deviation of the random parameter, and ζ_i is a vector of standard normal draws for i. For the effectiveness attributes, we expected a direction of preference (i.e., respondents were expected to derive positive utility from reductions in the number of new skin cancer cases and the number of skin cancer deaths), because of which we constrained the distribution of their parameters. That is, we assumed a log-normal distribution:

$$\delta_i = e^{\left(\mu_N + \sigma_N \zeta_{N,i}\right)}$$

For the tax attribute, we expected respondents to derive negative utility from a tax increase. Assuming a negative log-normal distribution (i.e., without shifting the distribution) may result in ‘exploding implicit prices’, however (Crastes dit Sourd, 2024). This potential issue was mitigated by ‘mu-shifting’ the point mass of the distribution of the tax attribute away from zero (Crastes dit Sourd, 2024):

$$\rho_i = -e^{(\mu_{tax})} - e^{\left(\mu_{tax} + \sigma_{tax}\zeta_{tax,i}\right)}$$

All models were estimated in R v.4.4.0, with the choice modelling package Apollo v.0.3.0 (Hess and Palma, 2019) and using the BGW algorithm (Bunch et al., 1993).

3. Results

The results from the MNL model, in which respondents had to choose

[2] The MNL results are robust to the inclusion of the respondents that were excluded from the main analyses, as well as to the exclusion of respondents who indicated to prefer no policy action regarding skin cancer prevention prior to the DCE (see Supplementary Material 7).

Table 2
Multinomial logit (MNL) model estimates with dummy-coded effect attributes.

Attribute level	AT		NL		ES	
	Coeff. (Rob. SE)	p-value	Coeff. (Rob. SE)	p-value	Coeff. (Rob. SE)	p-value
Policy attributes						
Information campaigns	0.3326 (0.0370)	<0.0001	0.1862 (0.0363)	<0.0001	0.2993 (0.0352)	<0.0001
Prohibition of sale tanning beds	−0.0179 (0.0367)	0.6266	0.0775 (0.0368)	0.0352	0.0891 (0.0342)	0.0091
Prohibition of solaria	0.0727 (0.0377)	0.0539	0.0819 (0.0400)	0.0404	0.1038 (0.0333)	0.0018
Price sunscreen 30 % lower	0.2810 (0.0354)	<0.0001	0.3169 (0.0363)	<0.0001	0.3693 (0.0339)	<0.0001
Free provision sunscreen in public areas	0.1065 (0.0400)	0.0078	0.1279 (0.0396)	0.0013	0.1284 (0.0356)	<0.0001
Free skin cancer detection app	0.1869 (0.0313)	<0.0001	0.1229 (0.0302)	<0.0001	0.1916 (0.0275)	<0.0001
Effect attributes						
Effect on N new cases of skin cancer per year						
−5 % (Ref.)	–	–	–	–	–	–
−10 %	0.0818 (0.0381)	0.0159	0.2003 (0.0405)	<0.0001	0.1681 (0.0360)	<0.0001
−15 %	0.1897 (0.0409)	<0.0001	0.3424 (0.0433)	<0.0001	0.3232 (0.0381)	<0.0001
−20 %	0.4020 (0.0417)	<0.0001	0.5948 (0.0438)	<0.0001	0.4078 (0.0388)	<0.0001
Effect on N deaths due to skin cancer per year						
−10 % (Ref.)	–	–	–	–	–	–
−15 %	0.0419 (0.0409)	0.1528	−0.0249 (0.0440)	0.2853	0.1632 (0.0417)	<0.0001
−20 %	0.1290 (0.0482)	0.0037	0.1879 (0.0482)	<0.0001	0.1699 (0.0474)	<0.0001
−25 %	0.2023 (0.0415)	<0.0001	0.3082 (0.0466)	<0.0001	0.4400 (0.0451)	<0.0001
*Additional tax**						
€36 per year (Ref.)	–	–	–	–	–	–
€72 per year	−0.3315 (0.0435)	<0.0001	−0.4825 (0.0462)	<0.0001	−0.3492 (0.0417)	<0.0001
€108 per year	−0.8131 (0.0650)	<0.0001	−1.0932 (0.0683)	<0.0001	−0.8400 (0.0616)	<0.0001
€144 per year	−1.2075 (0.0768)	<0.0001	−1.6108 (0.0854)	<0.0001	−1.0633 (0.0727)	<0.0001
ASC						
ASC right-hand alternative	−0.0913 (0.0286)	0.0014	−0.1278 (0.0289)	<0.0001	−0.0806 (0.0289)	0.0053
Model summary statistics						
N respondents	793		787		862	
LL (final)	−6080.74		−5803.96		−6647.37	
AIC	12193.49		11639.93		13326.75	
BIC	12308.06		11754.38		13442.66	

P-tests are two-sided for the policy attributes and one-sided for the effect attributes. Notes: *) The presented levels for the cost attribute are for Austria and the Netherlands and were adapted for Spain, as explained in the note to Table 1. Abbreviations: ASC=Alternative-Specific Constant, AT = Austria, Coeff. = Coefficient, ES=Spain, LL = Log-likelihood, NL=The Netherlands, Rob. SE = Robust Standard Error.

one of the two policy packages in each of the twelve choice tasks presented to them, are presented in Table 2. All policy measures were significantly and positively associated with the utility respondents derived from a policy package, except for both types of prohibition in Austria, which were not significantly associated with derived utility at the 95 % level. With respect to the effect attributes, the reductions in number of new skin cancer cases and skin cancer-attributable deaths were significantly and positively associated with the utility derived from a policy package. The only exception was the attribute level of a 15 % reduction in skin cancer deaths in Austria and the Netherlands. The tax increase attribute was significantly and negatively associated with the utility derived from a policy package for all levels in each country. Finally, the significant ASC parameters suggest left-right bias in each country (i.e., a higher choice probability for the left-hand alternative, ceteris paribus) (Boxebeld, 2024).

The relative attribute importance is presented in Fig. 2. As can be observed from the attribute-based normalization in Panel A, the tax attribute was the most important in respondents' choices in all three countries, and the difference in importance between the tax attribute and the other attributes was large. In the profile-based normalization in Panel B, the importance of each attribute is expressed as the proportion of the overall difference in utility between the most and least preferred policy package in a country accounted for by that attribute. Here, we do see differences between countries in the importance of the tax attribute, with the greatest importance in the Netherlands and the lowest in Spain. Regarding the two 'effectiveness attributes', the reduction of new cases was more important in respondents' choices than the reduction in deaths in both Austria and the Netherlands. In Spain, these two attributes were of similar importance. With respect to the policy measures, the preference structures of the three countries were rather similar. On average, lowering the price of sunscreen and information campaigns were more influential in respondents' choices than both types of prohibition, free sunscreen in public areas, and the free provision of a detection app. The most striking difference between countries is that the policy measures of information campaigns and the free provision of a detection app were less influential in respondents' choices in the Netherlands relative to Austria and Spain.

The results of the MMNL models, which accommodate random heterogeneity in preferences, are presented in Table 3. Starting values for the MMNL models were taken from the corresponding MNL models (see Supplementary Material 5). The results show there was significant heterogeneity in preferences for all the attributes in each country. Preference heterogeneity seems relatively stronger for the two types of prohibition, particularly in Austria and the Netherlands.

From the results, we derived the MRSs. The median, mean and standard error of the mean for the MRSs between the policy-specific attributes and the tax increase are presented in Table 4. The MRSs can be interpreted as the yearly increase in taxes respondents are willing to accept for the adoption of a particular policy measure. For instance, the median value of €12.77 for information campaigns in the Netherlands

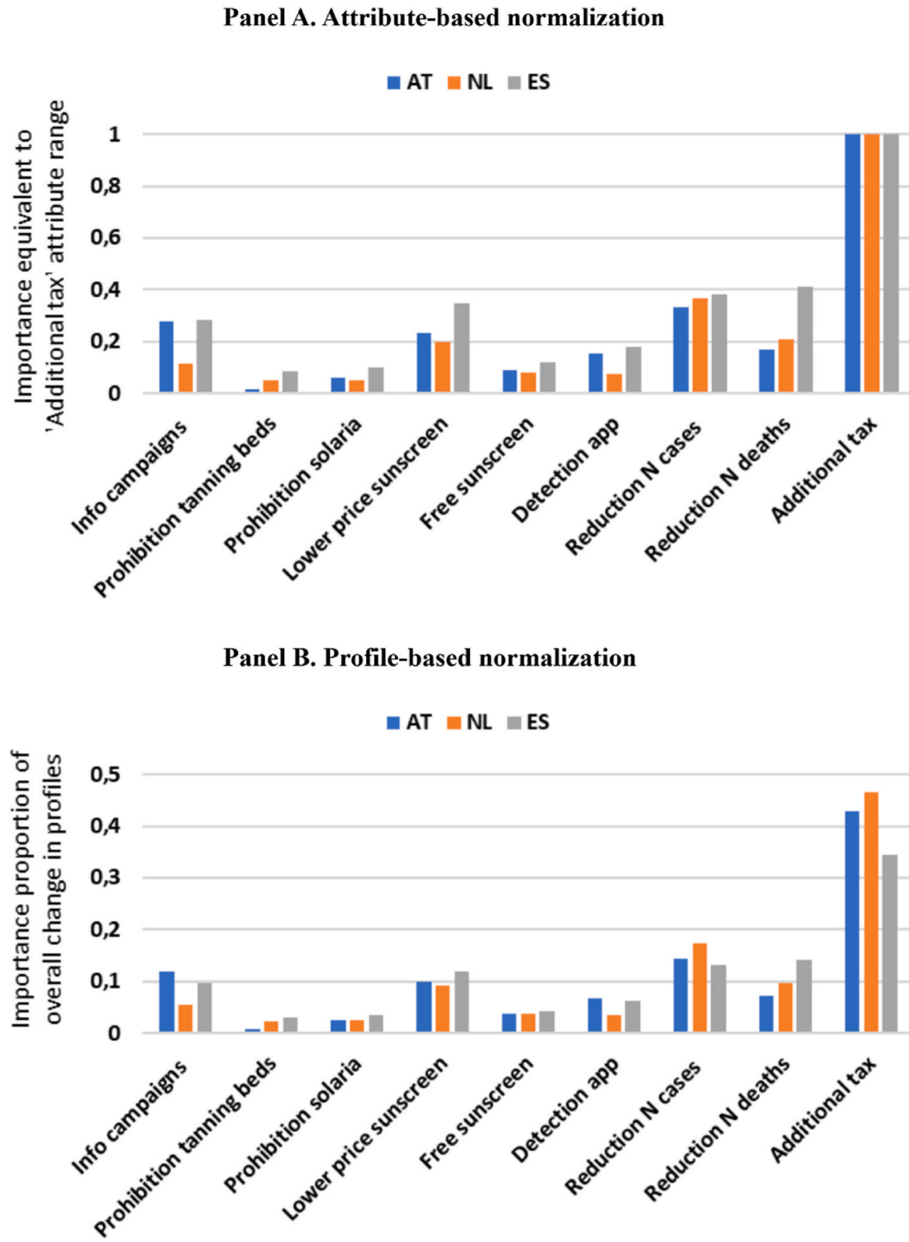

Fig. 2. Relative importance of the attributes by country.

indicates that the median respondent in the Netherlands is willing to accept a tax increase of €12.77 per year (i.e., a bit over €1 per month) if this results in the implementation of an information campaign. The much lower median values relative to the mean values indicate that the distributions of the MRSs for all attributes in all three countries are right-skewed.

The observations that arise when comparing the MRS estimates roughly correspond with the findings from the MNL models; from the six policy measures, information campaigns and a price reduction in sunscreen were most valued across the three countries, followed by a free skin cancer detection app. The prohibition of tanning bed sales and of solaria were least valued. Also, some differences between countries arise. Respondents in the Netherlands derived less value from information campaigns and a skin cancer detection app than those in Austria and Spain, in line with the relative attribute importance measures presented before. Also, respondents in Spain were least averse towards both types of prohibition, while respondents in Austria were most averse.

The MRS estimates for both effectiveness attributes by country are plotted in Fig. 3. It can be observed that the value of the MRS increases in the level of the effectiveness attributes for the reduction in new cases in Austria and the reduction in deaths in the Netherlands and Spain. In contrast, it decreases for the reduction in new cases in the Netherlands and Spain and for reduction in deaths in Austria. Similar to the policy-specific attributes, the median values are generally much lower relative to the mean values, indicating that the distributions of the MRSs for both effectiveness attributes in each of the countries are right-skewed. For reductions in the number of new cases, the MRS estimates are very similar for the Netherlands and Spain, while the mean MRS estimates in Austria are lower for lower values of the attribute and higher for higher values of the attribute. For reductions in deaths, the MRS estimates are rather similar for Austria and the Netherlands, although with opposite trends. While the median MRS estimates in Spain are similar to those in the other two countries, the mean MRS estimates are much higher. This indicates a substantially higher degree of skewness in the MRS distributions for this attribute in Spain compared with the other countries.

Table 3
Mixed multinomial logit (MMNL) model estimates.

Attribute level	AT		NL		ES	
	Coeff. (Rob. SE)	p-value	Coeff. (Rob. SE)	p-value	Coeff. (Rob. SE)	p-value
Policy attributes*						
Mean						
Information campaigns	0.6685 (0.0660)	<0.0001	0.4124 (0.0636)	<0.0001	0.5199 (0.0576)	<0.0001
Prohibition of sale tanning beds	0.0437 (0.0602)	0.4684	0.2417 (0.0598)	<0.0001	0.2048 (0.0521)	<0.0001
Prohibition of solaria	0.0292 (0.0653)	0.6549	0.0435 (0.0691)	0.5289	0.1453 (0.0535)	0.0066
Price sunscreen 30 % lower	0.5072 (0.0616)	<0.0001	0.6222 (0.0652)	<0.0001	0.5890 (0.0559)	<0.0001
Free provision sunscreen in public areas	0.1801 (0.0609)	0.0031	0.2597 (0.0640)	<0.0001	0.2426 (0.0529)	<0.0001
Free skin cancer detection app	0.4310 (0.0576)	<0.0001	0.3569 (0.0540)	<0.0001	0.3779 (0.0461)	<0.0001
SD						
Information campaigns	0.8971 (0.0858)	<0.0001	0.8252 (0.0835)	<0.0001	0.8943 (0.0716)	<0.0001
Prohibition of sale tanning beds	0.8127 (0.0863)	<0.0001	0.6607 (0.1038)	<0.0001	0.5668 (0.0874)	<0.0001
Prohibition of solaria	1.017 (0.0903)	<0.0001	1.0549 (0.0987)	<0.0001	0.6832 (0.0818)	<0.0001
Price sunscreen 30 % lower	−0.6079 (0.1045)	<0.0001	0.7106 (0.1015)	<0.0001	0.4425 (0.1102)	<0.0001
Free provision sunscreen in public areas	0.6187 (0.1029)	<0.0001	0.5977 (0.1046)	<0.0001	0.4576 (0.0989)	<0.0001
Free skin cancer detection app	0.6768 (0.0854)	<0.0001	−0.5456 (0.0962)	<0.0001	−0.3804 (0.0945)	<0.0001
Effect attributes*						
Mean						
Effect on N new cases of skin cancer per year #	−5.7920 (1.0871)	<0.0001	−3.0533 (0.6755)	<0.0001	−3.7025 (0.8167)	<0.0001
λ (transf. par.) N new cases	1.7109 (0.4090)	<0.0001	0.9432 (0.2724)	0.0005	0.9041 (0.3112)	0.0037
Effect on N deaths due to skin cancer per year #	−4.3020 (1.7571)	0.0072	−7.6417 (1.0429)	<0.0001	−5.3104 (1.1973)	<0.0001
λ (transf. par.) N deaths	0.6206 (0.6282)	0.3233	2.1073 (0.2988)	<0.0001	1.0963 (0.3929)	0.0053
Additional tax	−5.6066 (0.1338)	<0.0001	−5.1789 (0.1071)	<0.0001	−5.5866 (0.1334)	<0.0001
SD						
Effect on N new cases of skin cancer per year #	1.5839 (0.1601)	<0.0001	1.2166 (0.1039)	<0.0001	1.4089 (0.1231)	<0.0001
Effect on N deaths due to skin cancer per year #	2.4965 (0.2010)	<0.0001	2.2615 (0.1236)	<0.0001	2.8487 (0.1862)	<0.0001
Additional tax	2.7586 (0.1462)	<0.0001	2.7735 (0.1201)	<0.0001	2.5403 (0.1299)	<0.0001
ASC*						
Mean						
Right-hand alternative	−0.1395 (0.0428)	0.0011	−0.1879 (0.0407)	<0.0001	−0.1109 (0.0389)	0.0043
SD						
Right-hand alternative	0.6026 (0.0663)	<0.0001	−0.4192 (0.0762)	<0.0001	−0.6390 (0.0657)	<0.0001
Model summary statistics						
N respondents	793		787		862	
LL (final)	−5508.69		−5152.81		−6061.49	
AIC	11061.38		10349.61		12166.97	
BIC	11218.91		10506.98		12326.34	

P-tests are one-sided for the means of the effect attributes, and two-sided for all other coefficients. Notes: *) The random coefficients for the ASC and Policy attributes are specified to be normally distributed, those for the effects on the N of cases and N of deaths are specified to be positively lognormally distributed, and for the additional tax is specified to be mu-shifted and negatively lognormally distributed. #) This variable was Box-Cox transformed. Abbreviations: ASC=Alternative-Specific Constant, AT = Austria, Coeff. = Coefficient, ES=Spain, LL = Log-likelihood, NL=The Netherlands, Rob. SE = Robust Standard Error, SD=Standard Deviation.

Both before and after the choice tasks, respondents were asked whether they would recommend the government to adopt any policy measures to protect people against skin cancer.[3] In Fig. 4, the results are graphically presented. Prior to the DCE, most respondents are in favor of taking any policy action, ranging from 63.2 % in Austria and 71.0 % in the Netherlands to 83.1 % in Spain. These differences between countries are statistically significant at the 95 % level in a logistic regression, also after adjusting for country sample composition differences in terms of age, gender, and education level (see Supplementary Material 6). After the DCE, the shares of respondents in favor of taking any policy measures have increased with 7.9 %-point in Austria, 1.8 %-point in the Netherlands, and 3.1 %-point in Spain, reducing the difference in support between highest (i.e. Spain) and lowest (i.e., Austria) from 19.9 %-point to 15.1 %-point. This suggests that respondents adapted their preferences, based on their considerations of the policies and their effects while completing the DCE survey, in favor of taking policy action in all three countries, although this difference was not statistically significantly in the Netherlands.[4]

4. Conclusion and discussion

This study has examined public preferences for policies targeted at the prevention of skin cancer and differences in these preferences between three European countries with a varying incidence of (melanoma) skin cancer: Austria, the Netherlands and Spain. To our knowledge, it is the first study that examines preferences for collective skin cancer prevention measures, rather than for individual prevention measures. Its findings can be categorized into three overall findings.

[3] After the first time that respondents were asked this question, they were informed about the DCE design, asked to indicate for each of the included policy measures whether they thought the measure had already been in force in the year of data collection (i.e., 2023), they were presented with two instructional choice sets, and they completed the sequence of twelve choice tasks. Also, they were asked whether they themselves or anyone in their immediate surroundings had been diagnosed with skin cancer, and whether they had an occupation in which they were working outdoors (occasionally or frequently). Finally, before they were asked the question regarding their support for any policy action for the second time, respondents were asked to motivate their choices in the DCE, using two open-ended questions.

[4] According to a McNemar's Test for each country, the differences in proportions of people answering 'Yes' (as opposed to any of the other answer options) before and after the DCE are statistically significant at the 95 % level for Austria (McNemar's Chi-sq 29.84; p-value <0.0001) and Spain (McNemar's Chi-sq 8.19; p-value 0.0042), but not for the Netherlands (McNemar's Chi-sq 1.34; p-value 0.2466). After the DCE, the differences in support for policy action between Austria and the Netherlands are no longer statistically significant, while respondents in Spain again show a significantly higher level of support (see Table S9 in Supplementary Material 6).

Table 4
MRS estimates for the policy measures.

Attribute	AT			NL			ES		
	Median	Mean	Rob. SE	Median	Mean	Rob. SE	Median	Mean	Rob. SE
Information campaigns	41.20	90.99	14.30	12.77	36.60	6.55	29.43	69.37	11.78
Prohibition of sale tanning beds	0.60	5.94	8.14	6.09	21.45	5.54	8.90	27.32	7.33
Prohibition of solaria	0.32	3.97	8.93	0.34	3.86	6.16	4.76	19.39	7.64
Price sunscreen 30 % lower	33.47	69.03	10.71	27.43	55.21	7.44	50.90	78.58	11.26
Free provision sunscreen in public areas	6.06	24.51	8.33	7.33	23.04	5.82	13.05	32.37	7.58
Free skin cancer detection app	24.09	58.65	10.96	13.15	31.67	6.10	28.42	50.42	9.39

The estimates relate to the marginal rate of substitution (MRS) between each policy-specific attribute and the tax increase attribute. Abbreviations: AT = Austria, ES=Spain, NL=The Netherlands, Rob. SE = Robust Standard Error.

Firstly, the results from the choice models suggest that the policy measures, the effects on the number of new skin cancer cases and deaths, and the tax increase all played a role in respondents' choices in the three countries, except for the two types of prohibition policies in Austria. Furthermore, the tax attribute was the most influential attribute in each country, providing negative utility. Secondly, (almost) all policies were supported on average, and the preference structure was similar for the three countries. Respondents in the Netherlands valued information campaigns and the free provision of a skin cancer detection app less than respondents in Austria and Spain. Lowering the price of sunscreen was highly valued by respondents in all three countries, while both types of prohibition were less valued, particularly in Austria. This corresponds with previous studies that examined public preferences for preventive health interventions, which found that encouraging and less intrusive interventions receive more public support than discouraging and more intrusive interventions (Diepeveen et al., 2013; Dieteren et al., 2023; Mouter et al., 2022). The extent to which this is the case may vary by country and should also be considered in relation to (respondents' preferences towards) the effectiveness and costs of policy measures.

Finally, we find that the majority of respondents in each of the countries recommended the government to take policy measures to protect people against skin cancer. Public support for policy action was highest in Spain and lowest in Austria, both when asked before and after the DCE. However, the level of public support increased after the DCE, particularly in Spain and in Austria, so that the difference in public support between countries also decreased. This finding of policy support adapting over the course of the DCE survey provides an additional interesting insight,[5] that deserves further inquiry in future studies.

4.1. Policy implications

Policy action is generally supported by a large majority of respondents in all three included countries, while a minority (i.e., 18.0–22.6 % in Austria, 13.0 %–14.7 % in the Netherlands, and 5.6–8.5 % in Spain) would not recommend the government to take any policy action. As such, the governments of these countries are recommended to take policy action regarding this topic. When considering the implementation of preventive policies, governments are recommended to take measures that minimally increase the tax burden, since this is the most important (and disliked) attribute in respondents' preferences. This could be realized by means of implementing less expensive policies, or perhaps by reallocation of existing public resources rather than increasing the tax level.[6] At the same time, provided that the underlying assumption of fully compensatory decision-making holds, the MRS estimates show the extent to which respondents are willing to accept a tax increase for any specific measure and thereby indicate how much the government could spend on these policy actions while maintaining public support.

On average, almost all policy measures receive public support, but to varying extents. The two types of prohibition, the most intrusive policies, were the least supported policy measures. Governments are therefore recommended not to take these policies first. Dieteren et al. (2023) found a similar result in their DCE on policy measures promoting a healthy diet and suggested that implementing (less intrusive) policy measures may eventually raise support for more intrusive measures, referring to the stated preference literature surrounding tobacco and alcohol policies (Dieteren et al., 2023). Policies that are particularly recommended to be adopted (first) are lowering the price of sunscreen and information campaigns, as these policies were most preferred by respondents. While information campaigns may be generic and tailored towards everyone, their (cost-)effectiveness may be particularly high when targeted to groups with the highest risk of developing skin cancer or the greatest potential benefits of prevention, such as people with an outdoor occupation and children (Kasparian et al., 2009).

Finally, governments from countries for which no studies on preferences for collective skin cancer prevention policies are available yet may take away from this study that, across the three countries of study, there was broad support for less intrusive prevention policies. Nevertheless, the relationships between respondents' preferences and individual, institutional, cultural and other contextual characteristics remain unclear and, therefore, one should be cautious when extrapolating the results. Also, respondents in this study were informed about the specific mechanism through which policies would be financed (i.e., increasing taxes). Applicability and support for such mechanisms may vary across countries, which also should be considered when extrapolating the findings. For context-specific evidence about policy support for skin cancer prevention policies, conducting a study like this locally is strongly recommended.

4.2. Limitations and recommendations for future research

While the study has examined between-country differences in public preferences for skin cancer prevention policies, it has not attempted to explain these differences or to assess within-country (i.e., between-respondent) preference heterogeneity. Many individual- and country-level characteristics may contribute to preference heterogeneity within and between countries (e.g., Kasparian et al., 2009). Even though examining the role of such characteristics in public preferences is beyond the scope of our paper, it seems valuable to further explore

[5] Previous studies found that participation in a deliberation with others on the study topic (e.g., Jiang et al., 2023; Reckers-Droog et al., 2020) and information treatments in a DCE (e.g., Needham et al., 2018; Vanermen et al., 2021) may result in respondents adapting their attitudes and preferences. Also, some studies that used a DCE including an opt-out or status quo alternative (i.e., an unforced choice setting) found a change in the probability of choosing the opt-out or status quo alternative over the sequence of choice tasks (Boxebeld, 2024). These results, although investigated using different study approaches, relate to our findings.

[6] The latter would require that the respondents' willingness to allocate public budget to skin cancer prevention policies is higher than their willingness to do so for alternative public spending purposes, which is a condition that could be examined in future studies.

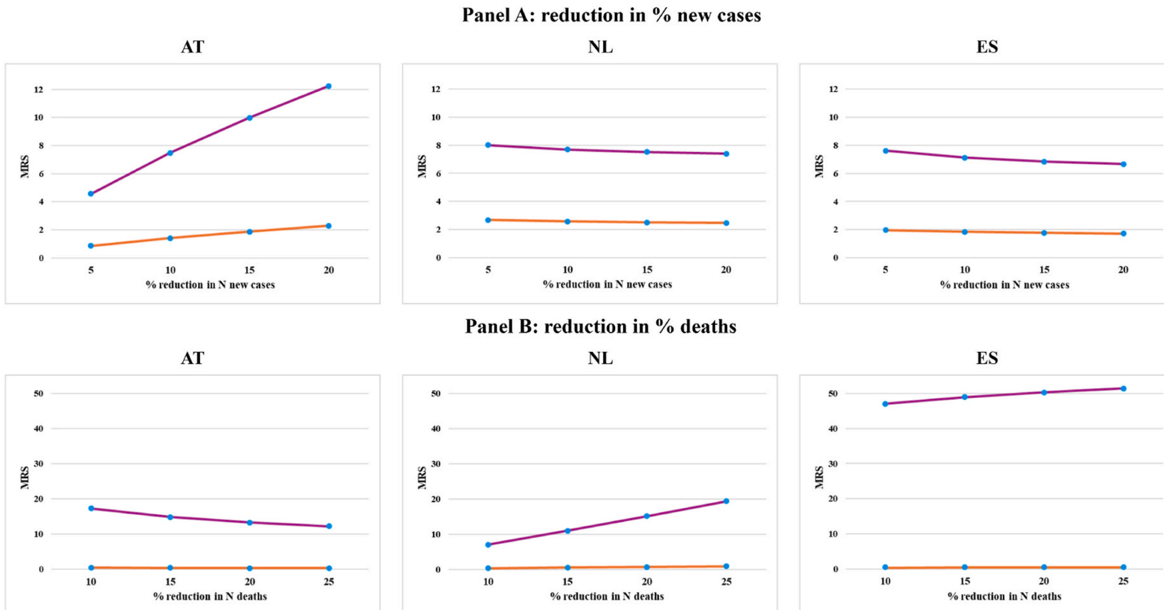

Fig. 3. MRS estimates for the effectiveness attributes.
The orange lines indicate the median MRS values, the purple lines indicate the mean MRS values. Abbreviations: AT = Austria, ES=Spain, NL=The Netherlands. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

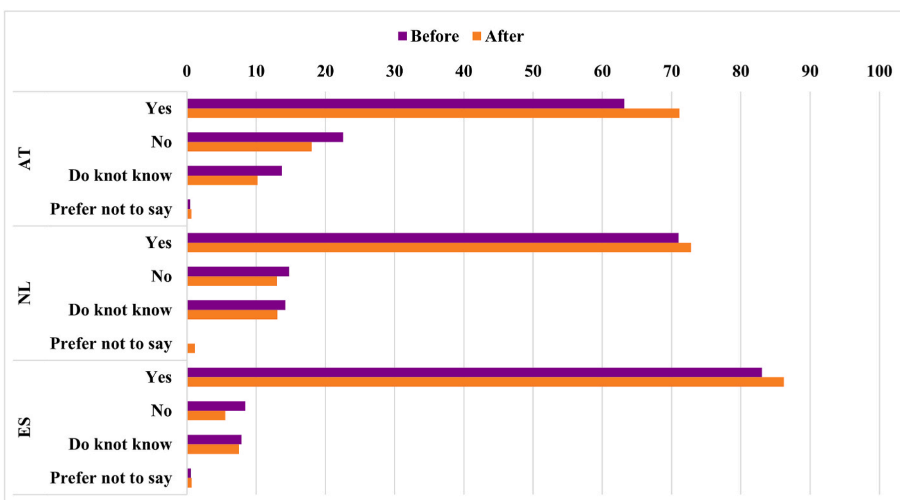

Fig. 4. Respondents' preferences for any policy action before and after the DCE.
Abbreviations: AT = Austria, ES=Spain, NL=The Netherlands.

preference heterogeneity regarding this topic. Also, we have excluded several policy measures from this DCE based on the pre-testing, such as the implementation of population-based screening programs and shading policies (see Supplementary Material 2). Future choice experiments may examine citizens' preferences towards these and perhaps other policy options, too.

Furthermore, in the DCE, we have presented respondents with a forced choice setting only. Future research may examine which factors influence respondents' choices for an opt-out or status quo alternative. Besides, since preferences may be endogenous to design characteristics of the DCE, future studies may examine the robustness of findings to design changes. For example, future studies may position the tax attribute in between the policy-specific attributes and the effectiveness attributes or change the specification of the payment vehicle or the visual presentation of attribute levels to examine the impact of these design traits on the importance of the tax attribute in respondents' choices.

Also, future studies may examine the robustness of the results to the analytical decisions made. For instance, due to limits to the available computational capacity, the simulation of the value of the log-likelihood function for the MMNL models is based on 5,000 Sobol draws. Following recommendations from recent research comparing simulation noise under different types of draws (Czajkowski and Budziński, 2019) and given the rather large number of random parameters in our MMNL models, we would ideally have used a larger number of (shuffled or scrambled) draws. Furthermore, to assure model convergence, we assumed uncorrelated random parameters in the estimation of our MMNL models, like most applied DCE studies in health economics. However, it has been recommended to allow for correlation between random parameters in an MMNL model (Mariel et al., 2021). Inclusion of all potential correlation patterns would substantially raise the number of parameters and complicate the model estimation. Finally, the estimates are based on the assumption of respondents employing fully compensatory decision heuristics. Previous studies have shown that respondents may not attend all attributes (Gonçalves et al., 2022) and, therefore, this assumption may not hold in practice. Even though attribute non-attendance (ANA) could be accounted for in the modelling, different methods of doing so are available (Gonçalves et al., 2022) and may lead to different results. Also, some studies argue it is difficult, or perhaps impossible, to disentangle the sources of attribute non-attendance (e.g., heuristics or true preferences) (Heidenreich et al., 2017), putting the analyst at risk of imposing rather than revealing preferences. For these reasons, we have not attempted to incorporate ANA in our models and acknowledge the potential bias resulting from this.

Furthermore, as applicable to all stated preference research, hypothetical bias may compromise the external validity of study findings (Haghani et al., 2021). To mitigate hypothetical bias, we have implemented a form of a consequentiality script in the introduction by stating that the results will be shared with the national ministry of health and national cancer foundation of the respective country. Nevertheless, we cannot exclude the possibility of hypothetical bias influencing the results. As another dimension of external validity, the study's results are time- and place-specific. For instance, stated preferences may be affected by respondents' psychological distance to the study topic (Veldwijk et al., 2019). Arguably, the psychological distance to the topic of study may be larger at the end of the year (when UV exposure is lowest), when data was collected, than in the summer (when UV exposure is highest). Besides, a variety of survey modes and sampling methods is available, with varying advantages and disadvantages (Mariel et al., 2021). The choice for online data collection may affect the data quality and representativeness of the study sample, even though its influence may be limited in practice (e.g., Determann et al., 2017). Also, we hope that this study in three countries inspires future research to examine citizens' preferences in other countries too, since preferences may depend on cultural, institutional, and other factors that differ between countries.

Finally, respondents in this study were asked to choose the most preferred policy package in each choice task of two packages, limiting the room for respondents to indicate their preferences towards particular combinations of policy measures. One of the respondents indicated that they would have liked to have the opportunity to compose a policy package of their preference, instead of choosing between two predetermined packages. To meet such demands, further research may make use of alternative preference elicitation methods to elicit citizens' preferences for skin cancer prevention policies. For example, Participatory Value Evaluation (PVE) seems a useful method in this context. Respondents in a PVE are asked to compose their most preferred policy package (called 'portfolio') from a set of policy measures, subject to a resource constraint. This allows them to express their preference towards particular combinations of policy measures and the extent to which resources are allocated to this policy area (Boxebeld et al., 2024).

5. Conclusion

This study explored public preferences for collective skin cancer prevention policies in three European countries. It provided governments with directions for publicly supported policy action to address the rising incidence of skin cancer and, with it, its increasing societal burden. The results suggested a large majority of citizens to support policy action against skin cancer. Less intrusive policy measures, such as reducing the price of sunscreen and information campaigns, are favored over more intrusive policy measures, such as the prohibition of solar bed sales and solaria. Also, while the study's results can inform governments with directions for policy action that are publicly supported, these should be complemented with additional information on the relative effects of the different policy measures, the relation between preferences and individual, institutional, cultural and other contextual factors, and citizens' argumentation, to form a more complete understanding of public support for collective skin cancer prevention policies.

CRediT authorship contribution statement

Sander Boxebeld: Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Niek Mouter:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Job van Exel:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Ethics approval

The study has received approval for data collection from the Research Ethics Review Committee from Erasmus School of Health Policy & Management (ESHPM) (reference: ETH2324-0087).

Role of the funding source

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Declaration of competing interest

SB, NM and JvE have no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2025.118155.

Data availability

Data will be made available on request.

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