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Cost vector effects in discrete choice experiments: Implications for the value of statistical life

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Abstract: This study investigates how the design of the cost attribute shapes stated preference estimates of the value of a statistical life (VSL). Using a discrete choice experiment (DCE) on willingness to pay (WTP) for cardiovascular mortality risk reductions, we implement a randomized design that varies the cost vector across three treatments, allowing us to compare monetary vectors that differ jointly in their range and spacing. Complementary diagnostics examine scope sensitivity and potential anchoring effects induced by information disclosure and feedback mechanisms. Point estimates of VSL differ by up to roughly 25% across treatments, but the reported between-treatment comparisons are not statistically significant. These results establish neither a detectable VSL effect nor equivalence across treatments. This contrast carries direct policy implications, since cost-benefit analyses and health regulations typically rely on point estimates of VSL rather than full distributions. Secondary diagnostics indicate less-than-proportional WTP scaling over the tested risk increments, while anchoring stimuli (revealing all attribute levels upfront, ordering cost levels from extremes, or providing feedback on comprehension questions) exert no detectable influence on choices or WTP. Taken together, the results highlight the need for clearer methodological guidance on cost attribute selection in stated preference research and underscore that seemingly modest design choices can shift welfare estimates in ways that are consequential for policy appraisal, while accounting for estimation uncertainty.

Keywords: cost vector effects, value of statistical life, behavioral biases, discrete choice experiment, mortality risk reduction

JEL codes: I12, D01, D61, Q51, C83, C93

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1. Introduction

The challenge of assigning monetary values to reductions in mortality risk – often summarized as the value of statistical life (VSL) – has long occupied scholars and policymakers ([Andersson & Treich, 2011](#); [Banzhaf, 2022](#); [Keller et al., 2021](#); [Shah et al., 2015](#); [Viscusi & Aldy, 2003](#)). Stated preference (SP) methods, such as discrete choice experiments (DCEs) and contingent valuation (CV), have emerged as influential tools in this domain by eliciting individuals' willingness to pay (WTP) for non-market goods, including lifesaving health interventions ([Alberini, 2019](#); [Hanley & Czajkowski, 2019](#)). Given the policy implications of VSL – whether for guiding public resource allocation, conducting cost-benefit analyses, or designing health regulations – securing valid and reliable estimates is paramount ([Bishop & Boyle, 2019](#)).

A central methodological consideration in DCEs concerns the design of attributes and their levels, which are combined to form the choice scenarios presented to respondents ([Lancsar & Louviere, 2008](#); [Mariel et al., 2021](#)). Among these attributes, cost occupies a particularly pivotal role, as it not only enables the estimation of WTP but also anchors the trade-off values for non-monetary attributes ([Ryan et al., 2007](#)). Yet the very feature that makes cost indispensable also renders it a potential source of bias. So-called cost vector effects arise when changes to the levels – or the spacing between those levels – of the cost attribute alter respondents' WTP in ways that deviate from theoretical expectations ([Carlsson & Martinsson, 2008](#); [Glenk et al., 2019](#); [Su et al., 2017](#)). Given the centrality of valid WTP estimates for VSL applications, understanding and mitigating such effects becomes especially consequential.

Early studies produced mixed evidence. For example, [Ryan and Wordsworth \(2000\)](#) using a split-sample design that varied the price attribute alongside other attributes, found that estimated coefficients were largely unaffected by changes in the cost vector, although mean WTP differed significantly in several cases. [Hanley et al. \(2005\)](#), by contrast, detected no significant shifts in preferences or WTP estimates across surveys with different cost vectors, suggesting that cost vector effects were neither pervasive nor universal.

A growing body of subsequent research, however, indicates that cost vector design can systematically influence valuation outcomes. [Carlsson and Martinsson \(2008\)](#) observed that higher absolute cost levels elevate marginal WTP estimates even when relative differences remain constant, and [Mørkbak et al. \(2010\)](#) demonstrated that raising the maximum price level increases the likelihood of a “choke price” effect, whereby respondents opt out more frequently

or exhibit systematically higher or lower WTP. Building on these findings, [Kragt \(2013\)](#) argued that individuals may focus on relative rather than absolute price differences, effectively anchoring their decisions to the specific cost levels presented.

Such anchoring behavior has since been corroborated in various other contexts. For instance, [Liesivaara and Myyrä \(2014\)](#) showed that price anchoring may disrupt market development for crop insurance products, while [Su et al. \(2017\)](#) documented similar patterns in WTP for rice with improved storage management. Broadening the scope, [Svenningsen and Jacobsen \(2018\)](#) examined cost vector effects alongside elicitation format and payment vehicle effects, concluding that each can influence preference structure and welfare estimates, while [Glenk et al. \(2019\)](#) reported that WTP rises as the magnitude of the cost vector increases. More recently, [Ahtiainen et al. \(2023\)](#) showed that cost vector effects persist even when the status quo alternative is associated with a positive cost, affecting the proportion of status quo choices and overall WTP distributions. [Martinet et al. \(2025\)](#) likewise found that reference cost shapes responses through anchoring bias and relative evaluation in forced-choice DCEs (i.e., those without an opt-out option).

While the evidence of the cost vector influence on welfare estimates has been proven in various contexts, some mitigation strategies have been proposed. [Börger et al. \(2025\)](#) found that clarifying opt-out reminders and including cheap talk scripts reduced the impact of different cost vectors on respondents' choices, and [Contini et al. \(2019\)](#) proposed a method in which respondents provide their own price interval as a reference point. [Lemos et al. \(2022\)](#) observed that informing respondents about price anchoring tendency can meaningfully attenuate its influence on valuation. Meanwhile, [Glenk et al. \(2024\)](#) suggested a diagnostic check wherein WTP estimates must align with the highest cost level to ensure that respondents' valuations reflect genuine trade-offs rather than artifacts of the experimental design. Taken together, these studies imply that insufficiently high cost levels may fail to "choke off" demand, while excessively large intervals between cost levels can distort WTP distribution and reduce the accuracy of final estimates.

Although best practices have begun to crystallize, such as using a wide but context-appropriate cost range, there remains no universally agreed-upon standard for cost attribute design ([Aravena et al., 2014](#); [Lancsar & Louviere, 2008](#)). This is partly due to the situational nature of DCEs, as attributes and levels must remain realistic and salient within a specific research context, making it difficult to prescribe a one-size-fits-all rule. Nonetheless, the literature consistently emphasizes that cost vectors should be chosen with care, as poorly

selected cost attributes can systematically bias WTP estimates and, by extension, policy advice derived from these estimates. Nonetheless, it is also worth noting that these effects are not exclusive to cost attributes and can extend to non-cost attribute range effects more broadly ([Bestard & Font, 2021](#)).

In this paper, we examine how cost vector selection affects preferences in the context of cardiovascular disease mortality risk reductions. We do so using a DCE to elicit respondents' willingness to pay for reducing mortality risk. To this end, our study incorporates several randomized treatments designed to examine cost vector effects, potential anchoring stimuli, and feedback mechanisms. Specifically, the experimental design varies in three dimensions: (1) the cost attribute vectors across three treatments, (2) whether the full set of attribute levels is pre-disclosed to respondents prior to DCE valuation tasks or withheld, and (3) providing or denying feedback on respondents' comprehension-question performance, allowing us to assess whether resolving misperceptions leads to more considered or systematically different valuations. These randomized assignments were block-managed to ensure balanced representation and adequate sample sizes across all treatment combinations, enabling us to isolate how each factor shapes stated preferences for mortality risk reductions.

The randomized design compares three cost vectors and examines information disclosure and feedback as secondary treatments. Point estimates of VSL differ by up to 25% across vectors, but the reported between-treatment tests are not statistically significant. This does not establish either a VSL treatment effect or equivalence. The vectors change range and spacing jointly, so the experiment does not identify their separate effects or an optimal granularity. The paired scope tests indicate less-than-proportional WTP scaling within all three cost-vector treatments. The anchoring and feedback manipulations produce no statistically detectable effects on the reported valuations.

By illustrating how cost vector range, scope, and anchoring effects can combine to influence VSL, our study underscores the necessity for clearer methodological guidelines in SP health valuation research. We propose that future studies adopt more systematic approaches to identifying cost vectors, use diagnostic checks for both anchoring and scope sensitivity, and employ experimental designs that mitigate potential distortions from learning and reference-dependent heuristics. These recommendations can help ensure that welfare measures (such as WTP or VSL estimates) – increasingly integral to policy decisions – reliably capture individuals' true preferences.

Following this introduction, Section 2 describes our study design and data collection procedures, detailing the questionnaire structure, the experimental treatments, and the sampling approach. Section 3 presents the econometric framework, including the specification of our mixed logit model with correlated random parameters and the methods used to derive WTP and VSL estimates. Section 4 reports empirical results, examining the cost vector and underlying behavioral effects. In Section 5, we discuss these findings in the context of existing research and highlight implications for improving the reliability of stated preference methods. Finally, Section 6 concludes by summarizing our main contributions, noting study limitations, and suggesting avenues for future research.

2. Study design and data collection

In this section, we describe the DCE design following the DIRECT checklist to provide a clear and structured description of the experimental setup, attributes, and survey implementation ([Ride et al., 2024](#)).

2.1. Purpose and rationale

In this study, we aim to examine how the selection of cost vectors may influence stated valuations of a hypothetical health intervention aimed at reducing cardiovascular mortality risk. The research question stems from concerns that design features of the cost attribute, particularly the range and distribution of bid levels, may systematically affect respondents' choices and, consequently, the validity of derived measures. To this end, we implement a randomized controlled experimental design in which alternative cost vectors are systematically varied across the DCE. This allows us to identify whether and how such design features affect stated preferences, as well as their downstream implications for WTP for reductions in cardiovascular mortality risk, and, ultimately, for the derivation of VSL estimates.

2.2. Attributes and levels

Our DCE design incorporates only two attributes: (1) the scale of cardiovascular mortality risk reduction, quantified as 1, 2, or 4 fewer deaths per 1,000 people over a span of 10 years, and (2) the annual cost associated with each option. The attributes and their levels are summarized in Table 1. This simplified design was deliberately chosen to isolate the effect of cost vectors in relation to mortality risk reductions. Although DCEs often include additional attributes, such as morbidity outcomes, implementation lags, or quality-of-life impacts, introducing these elements could obscure the interpretation of cost vector effects. For this

reason, we opted for a deliberately minimal attribute structure, reducing task complexity and holding the non-cost attribute structure constant across treatments. This approach allows for a clearer assessment of how cost-vector selection influences WTP toward mortality risk reductions and resulting VSL estimates.

Table 1. DCE attributes and levels

Attributes	Levels		
Mortality risk reduction	Level 1: 1 fewer death per 1,000 people over the next 10 years Level 2: 2 fewer deaths per 1,000 people over the next 10 years Level 3: 4 fewer deaths per 1,000 people over the next 10 years		
Annual cost	Low-Cost Vector (LC): Level 1: 50 PLN Level 2: 100 PLN Level 3: 150 PLN Level 4: 200 PLN Level 5: 250 PLN Level 6: 300 PLN	Medium-Cost Vector (MC): Level 1: 100 PLN Level 2: 200 PLN Level 3: 300 PLN Level 4: 400 PLN Level 5: 500 PLN Level 6: 600 PLN	High-Cost Vector (HC): Level 1: 200 PLN Level 2: 400 PLN Level 3: 600 PLN Level 4: 800 PLN Level 5: 1 000 PLN Level 6: 1 200 PLN

Note: According to OECD data on purchasing power parity (PPP) for 2022, 1 PLN had the equivalent purchasing power of 0.56 USD (USA) or 0.384 EUR (EA-19).

Regarding cost vectors – which constitute the primary experimental manipulation in this study – the survey utilizes three categories: low (LC), medium (MC), and high (HC). Each category differs systematically in both scale and step size, increasing in increments of 50, 100, and 200, respectively. This yields cost ranges of 50–300 PLN (LC), 100–600 PLN (MC), and 200–1,200 PLN (HC). As a result, the selected cost vectors vary by the starting point, choke-off point, and intervals. Participants are randomly assigned to one of these cost vector treatments and are exposed exclusively to that version throughout the choice tasks. This randomization allows us to assess whether different cost vectors elicit divergent WTP responses – and, by extension, whether cost levels themselves serve as anchors.

The chosen cost vector levels were determined through pretesting with focus groups and are informed by prior research on the valuation of cardiovascular risk reduction in Poland ([Bartczak et al., 2021](#)). While the majority of respondents during qualitative pretesting expressed a WTP to reduce mortality risk by 1 in 1,000, ranging from approximately 100 to 150 PLN, some reported valuations were approaching zero or were substantially exceeding these amounts. This considerable preference heterogeneity motivated the inclusion of a wide and systematically varied set of cost vectors to adequately capture the full range of respondents' valuations.

Ideally, a study would incorporate a wide-ranging cost vector with a low defined starting point, a high choke-off point, and granularly spaced intermediate values. However, achieving this would require a substantially larger experimental design and, consequently, a much larger sample size. Researchers therefore face a trade-off, often settling on a cost vector with relatively few (several) elements – a modest number given that most DCEs include several other attributes, each with multiple levels ([Glenk et al., 2019](#)). As such, the cost vector can appear somewhat artificial, particularly in light of the broader absence of standardized guidelines for selecting cost elements in SP studies. Because cost vectors are typically designed a priori, without precise knowledge of the underlying demand curve, decisions regarding the initial and final values largely reflect the researcher's own judgement ([Hanley et al., 2005](#)).

Notably, in the absence of clear and explicit guidelines for selecting cost vectors, all of the cost vectors employed in this study could, in principle, be regarded as valid. At the same time, some of these specifications might be considered suboptimal or even incorrect from a methodological standpoint. However, without well-defined criteria that distinguish an appropriate cost vector from a poorly chosen one, it is difficult to draw a clear line between what should be considered good or bad practice in this context. Against this backdrop, our analysis provides empirical evidence on how variation in these cost vectors – arguably selected with limited precision – can meaningfully influence final outcomes.

2.3. Experimental design

We employ a Bayesian D-efficient experimental design ([Huber & Zwerina, 1996](#); [Sandor & Wedel, 2001](#)) to generate 36 choice tasks, divided into 3 blocks (of 12 choice tasks each). The design maximizes the precision of parameter estimation by incorporating prior information (initially set to zero, then updated with pilot data). Each participant is randomly allocated to one design block, ensuring balanced representation across cost treatments.

However, since our hypothesis assumes that preferences vary across cost vectors, different priors should ideally be used for each cost treatment. This, in turn, necessitates accounting for the potential differences in experimental design. To address this challenge, we implement a tailored solution. Initially, all three cost treatments shared a common Bayesian D-efficient design, with priors set to zero (with 3 blocks, each containing 12 choice tasks). After piloting a first wave and obtaining updated priors for each treatment subsample, we refined the design by generating three separate D-efficient designs – each containing 1 block with 12 choice tasks – tailored to the low, medium, and high-cost vector treatments. These were

then integrated into a final (joint) experimental design, structured as distinct 3 blocks, where the monetary values were adjusted based on the assigned cost vector for each respondent. Consequently, each cost vector treatment uses the same design, where respondents could encounter a block that either used the priors specific to their cost vector or incorporated priors derived from other cost treatments. This approach mitigates potential discrepancies introduced by the experimental design, ensuring a more balanced and robust estimation of preferences across cost treatments ([Bliemer & Rose, 2011](#)).

2.4. Survey design

Designing a SP survey for non-market valuation requires rigorous preparation and adherence to recognized best practices ([Johnston et al., 2017](#); [Lancsar et al., 2017](#); [Lancsar & Louviere, 2008](#); [Mariel et al., 2021](#)). Following these guidelines, and drawing on prior research on WTP for mortality risk reductions ([Bartczak et al., 2021](#); [Desaigues et al., 2011](#); [Hammitt & Tunçel, 2023](#); [Krupnick et al., 2002](#)), we developed a comprehensive questionnaire to examine how the selection of cost vectors may influence stated valuations of a hypothetical health intervention aimed at reducing cardiovascular mortality risk. Our design introduces explicit adaptations to foreground the role of the cost vector.

The questionnaire begins by explaining the purpose of the study and highlighting its potential policy relevance. Respondents are informed that aggregated findings will be made available to governmental and research institutions, thereby emphasizing consequentiality perceptions ([Carson & Groves, 2007](#); [Vossler et al., 2012](#)). After confirming that the responses will remain anonymous, the survey collects standard demographic information (sex, age, education, region, and household size) and household income data. These questions establish the socio-economic context necessary for interpreting WTP differences and controlling for heterogeneity in subsequent analyses.

We then assess respondents' current health status using the EQ-5D-5L module, which captures dimensions like mobility, self-care, usual activities, pain/discomfort, and anxiety/depression. Additional questions probe the frequency of doctor visits and the presence of chronic or cardiovascular conditions, including any familial history. Further items address the frequency of alcohol, nicotine, drug and psychoactive substances use, as well as the frequency and duration of physical activity, alongside self-reported weight and height. By prompting participants to reflect on their own health, we aim to heighten engagement with the concept of mortality risk. The survey then offers a concise overview of cardiovascular

diseases in Poland, underscoring its predominant share of total mortality, and briefly outlines the principal risk factors (e.g., genetic predisposition, dietary habits, smoking).

Next, to aid respondents in grasping (cardiovascular) mortality risk, we employ a visual grid that depicts black squares (deaths) and white squares (survivors) out of 1,000 people over the next 10 years. The average cardiovascular mortality risk in Poland, set at 47 deaths per 1,000 people per decade, is introduced using this visual aid. Respondents then complete three comprehension questions (e.g., translating risk figures into proportions or comparing relative risk levels) to verify their comprehension of the core concepts. At this stage, we additionally introduce a supplementary treatment (orthogonal to the cost vector treatments) designed to examine whether corrective feedback shapes risk perception or decision-making. The rationale rests on the premise that respondents who misunderstand baseline risk may anchor their valuations on mis-calibrated beliefs, potentially biasing WTP estimates. We hypothesize that respondents who received feedback might refine their understanding of probabilities and thus display more internally consistent risk valuations. Conversely, those who learned they misunderstood a question might experience frustration or mistrust in the survey, potentially dampening or biasing their subsequent WTP. By providing immediate feedback to a randomly assigned subset of respondents (while withholding it from the remainder), we are able to isolate the effect of comprehension awareness on subsequent choices, and assess whether resolving misperceptions leads to more considered or systematically different valuations ([Andersson & Svensson, 2008](#); [Welling et al., 2023](#)).

To further anchor mortality risk in a familiar context, we also present information on statistical life expectancy derived from gender- and age-specific actuarial life tables, given that framing risk reduction benefits in terms of life expectancy gains has been shown to be particularly persuasive ([Grisolía et al., 2018](#)). Overall, the entire risk comprehension module aims to ensure that participants are adequately informed about their baseline risk and that comprehension is reinforced through the use of visual aids ([Corso et al., 2001](#); [Marceta et al., 2025](#); [OECD, 2025](#)).

Following the comprehension module, participants are prompted to estimate their own mortality risk relative to the national average. They are asked to indicate whether they think their personal risk is higher, lower, or broadly similar to the national baseline – or indicate uncertainty – while being reminded of modifiable and non-modifiable factors that could influence actual risk. They are further asked to quantify their subjective risk numerically, in accordance with the previously introduced metric of deaths per 1,000 people per decade. This

reflective exercise encourages meaningful introspection about personal health circumstances before respondents proceed to evaluate hypothetical interventions.

Participants then engage in the DCE, evaluating a hypothetical drug designed to prevent some deaths from cardiovascular diseases. The drug is presented as having no side effects, receiving endorsements from official health agencies, and being capable of reducing mortality risk and eliminating hospitalizations due to cardiovascular events over the next decade. Each DCE choice task offers participants two different drug profiles to compare, alongside a status quo option that incurs zero cost and offers no improvement in mortality risk. An example of a choice task is presented in Table 2.

Table 2. An example of a DCE choice task

Which of the options presented below do you think is best for you? Please treat each situation independently of the others.			
	Drug A	Drug B	Resignation from taking the drug
Mortality risk reduction	2 fewer deaths per 1,000 people over the next 10 years	4 fewer deaths per 1,000 people over the next 10 years	The risk of dying from cardiovascular diseases will remain the same
Annual cost	100 PLN	300 PLN	0 PLN
Your choice:	☐	☐	☐

Prior to the DCE, another treatment (orthogonal to previous ones) is introduced. Specifically, half of the respondents in each cost-treatment group are presented with an additional screen listing all possible levels of the risk-reduction and cost attributes prior to seeing any valuation tasks, while the remaining half proceed directly to the valuation exercise without prior exposure. This treatment is designed to investigate whether the advance disclosure of attribute levels mitigates or exacerbates cost vector effects, building on the broader literature concerning ordering effects and information disclosure in stated preference studies ([Day et al., 2012](#)). The rationale draws on well-established evidence that single bid values can act as cognitive anchors, inadvertently shaping respondents' WTP before they engage with the valuation tasks ([Boyle et al., 1997](#); [Meyerhoff & Glenk, 2015](#)). What remains less clear, however, is whether presenting the full range of cost levels – rather than a single bid – amplifies this anchoring effect, attenuates it, or introduces an altogether different form of preference distortion. On the other hand, advance exposure to the full attribute space may afford respondents the opportunity to deliberate and refine their preferences prior to valuation,

potentially yielding more stable and internally consistent responses. Disentangling these competing mechanisms is of methodological relevance, as it bears directly on how much information should be conveyed to respondents at the outset of a DCE.

Finally, the survey concludes with debriefing questions to gauge the perceived realism and clarity of the scenarios, as well as the respondents' sense of survey consequentiality. We also confirm whether participants felt they understood the risk attributes well enough to provide meaningful valuations.

This layered design aims to isolate and identify potential behavioral biases related to cost vector selection. By combining DCE tasks and strategic treatments (exposing to different cost vectors, disclosing or withholding attribute levels in advance, and offering or denying feedback on comprehension), we gather a rich set of observations that illuminate how respondents construct WTP for mortality risk reductions – and what might systematically distort those valuations.

Before full-scale data collection commenced, the survey was subjected to multiple rounds of qualitative testing to ensure its robustness and clarity. Initially, four medical experts conducted an expert review to verify the accuracy of the descriptions of cardiovascular diseases and the dimensions of associated risks. Following this, three focus groups consisting of individuals with varied demographic profiles were convened to work through a preliminary version of the questionnaire. Their feedback provided valuable insights on the clarity of the questions and the plausibility of the cost levels presented. Additionally, individual interviews were conducted with a language specialist and two general respondents. These verbal-protocol sessions were instrumental in refining the final wording of questions related to risks and costs. These comprehensive and iterative steps ensured that the final instrument was clear and understandable to non-experts, minimized cognitive load, and avoided the use of overly technical language or ambiguous phrases. Notably, the survey instrument and research idea were also consulted with health economics and choice experiment experts at several workshops and conferences ([Zawadzki et al., 2024](#)).

2.5. Sample and data collection

The study was administered through a computer-assisted web interviewing (CAWI) platform in March 2023, yielding 1,299 usable responses from Polish residents. This approach provided a cost-effective and flexible means of reaching a broad cross-section of the population while offering advanced tools for randomization and response tracking. Potential participants

(from the CAWI panel) received an online invitation explaining the general nature of the study (i.e., research on health and mortality risk) and assuring them of data confidentiality. Respondents who agreed to participate accessed the questionnaire via a secure link, where the survey's internal randomization engine assigned them to the relevant treatments.

In keeping with standard ethical guidelines for survey-based research, all participants provided informed consent at the outset. They were reminded that their participation was voluntary and that they could exit at any stage without penalty. Each respondent was compensated through the survey panel provider according to standard rates.

To ensure demographic diversity, we implemented quota-based recruitment, aligning the sample with national statistics for sex, age, education, and region. Table 3 presents the sociodemographic breakdown, confirming that the final sample closely reflects the broader Polish adult population. In total, 416 respondents were assigned to the low-cost (LC) vector, 433 to the medium-cost (MC) vector, and 450 to the high-cost (HC) vector, with further splits within each group for attribute disclosure and comprehension feedback treatments. Additional details on sample characteristics and stratification are provided in Table 3, confirming that each treatment group mirrors the broader Polish population across key sociodemographic variables.

To enhance the quality of data collected, several mechanisms were systematically implemented throughout the survey process. First, progress bars and time reminders helped maintain engagement and alert participants to the approximate length of the survey. Second, completion time thresholds were established to flag responses that were submitted too quickly, which could indicate minimal engagement with the survey questions, often referred to as "speeding." In addition to monitoring completion times, attention and comprehension checks were integrated throughout the survey. These were not limited only to the main risk-comprehension tasks. Reminders were also interspersed to prompt respondents to focus on the trade-offs required by the survey tasks, aiming to mitigate careless or inattentive responses. Furthermore, technical support was available, offering clarification on question wording and study objectives to help respondents resolve misunderstandings promptly, thereby maintaining the integrity and accuracy of the data collected.

Upon survey completion, responses were compiled and subjected to basic filtering. Observations flagged for excessive speeding or major inconsistencies in demographic data were removed prior to analysis. After final checks, 1,299 valid responses remained, forming the dataset used for the subsequent econometric modeling.

Table 3. Representativeness of the sample

		Full sample	Low cost	Medium cost	High cost
N	Total sample	1299	416	433	450
Sex	Female	53.27%	54.81%	53.35%	51.78%
	Male	46.73%	45.19%	46.65%	48.22%
Age group	18-24	9.70%	9.38%	9.24%	10.44%
	25-44	40.03%	39.42%	41.80%	38.89%
	45-64	32.10%	32.93%	31.64%	31.78%
	65+	18.17%	18.27%	17.32%	18.89%
Education	Incomplete Primary or No School Education	0.46%	0.72%	0.46%	0.22%
	Completed Primary Education	2.00%	2.40%	2.54%	1.11%
	Lower Secondary Education	1.08%	0.96%	1.15%	1.11%
	Basic Vocational Education	11.70%	12.50%	10.62%	12.00%
	Secondary or Post-secondary Non-tertiary Education	38.57%	35.10%	39.03%	41.33%
	Higher Education	46.19%	48.32%	46.19%	44.22%
Region (voivodeship)	dolnośląskie	7.16%	7.21%	6.93%	7.33%
	kujawsko-pomorskie	5.16%	5.53%	5.54%	4.44%
	lubelskie	5.77%	5.29%	5.31%	6.67%
	lubuskie	2.16%	2.40%	1.85%	2.22%
	łódzkie	6.62%	6.25%	7.39%	6.22%
	małopolskie	6.93%	6.49%	6.93%	7.33%
	mazowieckie	15.09%	15.87%	16.17%	13.33%
	opolskie	2.62%	2.16%	3.23%	2.44%
	podkarpackie	4.93%	6.25%	3.70%	4.89%
	podlaskie	3.23%	3.61%	2.77%	3.33%
	pomorskie	7.08%	6.25%	9.01%	6.00%
	śląskie	14.47%	12.98%	13.86%	16.44%
	świętokrzyskie	2.23%	1.68%	2.77%	2.22%
	warmińsko-mazurskie	4.08%	4.09%	3.93%	4.22%
	wielkopolskie	8.70%	10.34%	7.39%	8.44%
	zachodniopomorskie	3.77%	3.61%	3.23%	4.44%
Household size	1	13.47%	13.94%	15.01%	11.56%
	2	36.80%	36.30%	36.49%	37.56%
	3	23.71%	23.56%	23.09%	24.44%
	4	16.32%	15.14%	15.47%	18.22%
	5+	9.70%	11.06%	9.93%	8.22%

Overall, this sampling and administration process aligns with best practices in stated preference research by ensuring a balanced, sufficiently large participant pool, employing rigorous randomization, and implementing careful data-quality protocols. The resulting dataset provides a robust foundation for investigating how cost vector design impact respondents' WTP for a hypothetical cardiovascular risk-reducing intervention.

3. Econometric framework

DCEs are a well-established SP method for estimating individuals' valuations for non-market goods, rooted in a utility-maximization paradigm that integrates Lancaster's consumer theory ([Lancaster, 1966](#)) with random utility theory ([McFadden, 1973](#)). Within this framework, an individual i considering a set of alternatives in a choice situation t is assumed to select the alternative j that maximizes the individual's overall utility, denoted by:

$$U_{ijt} = X_{ijt}\beta_i + \varepsilon_{ijt} \quad (1)$$

where X_{ijt} is a vector of observed attributes describing alternative j , β_i is a vector of preference parameters specific to individual i , and ε_{ijt} is a random error term capturing unobserved utility components.

To accommodate heterogeneity in preferences and relax the independence-from-irrelevant-alternatives (IIA) assumption inherent in the simple multinomial logit, we adopt a mixed logit (also known as a random parameters logit) specification ([Train, 2009](#)). In this model, the parameter vector β_i is drawn from a specified probability distribution $f(\beta | \theta)$, where θ represents distributional parameters (e.g., means, standard deviations, or correlations). For each choice situation t , the probability that individual i selects alternative j from a set of J alternatives is written as:

$$p_{ijt}(\theta) = \int \left[\frac{\exp(X_{ijt}\beta)}{\sum_{j=1}^J \exp(X_{ijt}\beta)} f(\beta_n | \theta) \right] d\beta_n \quad (2)$$

Because there is no closed-form solution for this integral, we approximate it through simulation. Specifically, we draw from the distribution $f(\beta | \theta)$ 10,000 times (scrambled Sobol draws) and average the resulting choice probabilities to obtain simulated likelihood estimates ([Czajkowski & Budziński, 2019](#); [Hole, 2007b](#)).

Following standard practice in health and environmental valuation ([Hensher & Greene, 2003](#); [Mariel et al., 2021](#)), we allow the cost parameter to follow a lognormal distribution to ensure that marginal utilities for cost lie on the expected side of zero (i.e., a negative coefficient for a price-like attribute). Meanwhile, the coefficients for mortality risk reductions and alternative-specific constants (ASCs) are assumed to follow a normal distribution.

To account for correlations among random coefficients, reflecting the possibility that unobserved factors influencing one parameter may be related to unobserved factors affecting

others, we allow the random coefficients to be correlated ([Mariel & Artabe, 2020](#)). Therefore, our approach can be summarized as the mixed logit model with correlated random parameters.

From the estimated parameter distributions, we derive WTP for specific attribute changes using a ratio of coefficients. In a simple two-attribute model (risk reduction and cost), the WTP for a given level of risk reduction relative to the reference level is:

$$WTP = -\frac{\beta_{Risk}}{\beta_{Cost}} \quad (3)$$

where β_{Risk} is the estimated coefficient for a given level of mortality risk reduction and β_{Cost} is the estimated coefficient for the cost attribute. The negative sign reflects the fact that cost typically has a negative sign in utility functions. In the mixed logit model, both coefficients vary across respondents, so (3) defines an individual $WTP_i = \frac{\beta_{Risk,i}}{|\beta_{Cost,i}|}$. The cost coefficient enters as the negative of a lognormally distributed variable, which keeps its sign negative for every respondent. The population distribution of WTP_i describes preference heterogeneity. We characterize it by its median across respondents, obtained by simulation. We do not use the ratio of median or mean coefficients, because a quantile or moment of a ratio generally differs from the ratio of the corresponding quantiles or moments. The median is also robust to the heavy tails that arise when the lognormal cost coefficient approaches zero.

We rely on simulation methods, specifically the Krinsky-Robb procedure ([Krinsky & Robb, 1991](#)), for constructing these intervals ([Hole, 2007a](#)). The procedure has two nested loops. The outer loop takes 10,000 draws of the full parameter vector from a multivariate normal distribution whose mean is the vector of mixed logit point estimates and whose covariance is the asymptotic variance-covariance matrix of the estimator. Each draw contains the means of the random coefficients and the elements of the Cholesky factor that governs their correlation. The inner loop, conditional on each outer draw, simulates coefficients for 10,000 respondents from the implied population distribution, applies the exponential transformation to the cost coefficient, computes individual WTP for every risk reduction level, and takes the median over the simulated respondents. The 10,000 resulting values of median WTP approximate the sampling distribution of this estimator. We report the mean of these draws as the point estimate, together with their standard deviation as the standard error and 95% confidence intervals given by the 2.5th and 97.5th percentiles. The median is thus taken over simulated respondents within each draw, while the mean, standard error, and percentiles are taken over the 10,000 draws of this median.

To translate WTP for a given mortality risk reduction into the VSL, we follow a common approach in the VSL literature ([Andersson & Treich, 2011](#); [Kniesner & Viscusi, 2019](#)). Specifically, if $WTP(\Delta Risk)$ is the annual willingness to pay for lowering mortality risk by $\Delta Risk$, we convert it into a VSL by dividing by the change in risk and adjusting for the relevant time horizon. Because the cost attribute is coded in hundreds of PLN, we multiply the coefficient ratio by 100. The two risk dummies represent reductions of two and four deaths per 1,000 relative to the one-death reference level, corresponding to additional reductions of one and three deaths per 1,000, so we divide each WTP by the corresponding $\Delta Risk$ expressed as a probability. For an annual cost that persists over 10 years, the VSL for a risk reduction from, say, 1/1,000 to 4/1,000 (i.e., a $\Delta Risk=3/1,000$ shift) can be expressed as:

$$VSL = \frac{WTP(\Delta Risk)}{\Delta Risk} \times 10 \quad (4)$$

This scaled figure represents the implied monetary value placed on preventing one statistical death, based on the incremental gain in survival probability and the payment period. The multiplier of 10 sums the ten annual payments without discounting and therefore assumes a zero discount rate. We apply (4) to each of the 10,000 draws of WTP and summarize the resulting VSL distribution in the same way.

In sum, our econometric framework is designed to capture individual heterogeneity in preferences for reducing cardiovascular mortality risk. By combining a mixed logit approach with a simulation procedure that keeps preference heterogeneity separate from estimation uncertainty for obtaining WTP and VSL estimates, we can assess the degree to which cost vector design is associated with changes in these valuations and their precision.

4. Results

Our analysis primarily investigates whether the selection of various cost vectors in DCEs yields different results and how those differences influence VSL estimates. To explore this, we estimated three separate mixed logit models with correlated random parameters, each corresponding to a subsample of respondents exposed to low-cost (LC), medium-cost (MC), or high-cost (HC) vectors. To capture baseline preferences for choosing an alternative that reduces mortality risk, we included an alternative-specific constant (ASC) in the models. Additionally, we decomposed the risk attribute into two binary (dummy-coded) variables, representing reductions of two and four fewer deaths per 1,000 people over 10 years (with a reduction of one death per 1,000 serving as the reference category). This specification

allows us to test for scope sensitivity ([Andersson et al., 2016](#); [Dugstad et al., 2021](#)) – specifically, whether the VSL estimate derived from WTP for a reduction of one death aligns with the VSL estimate derived from the WTP for a reduction of three deaths $0F^1$. The results, detailed in Table 4, provide insights into the relationship between cost variation and VSL estimates.

To calculate VSL, we first simulated WTP values separately for each model, corresponding to reductions of two and four fewer deaths per 1,000 people. The VSL was then calculated by dividing each WTP value by the respective change in risk reduction compared to the baseline level and multiplied by ten to account for the annual cost spanning a decade. These values, denoted as $VSL_{\Delta Risk=1}$ and $VSL_{\Delta Risk=3}$, follow a widely adopted straightforward approach suggested by the literature ([Andersson & Treich, 2011](#); [Kniesner & Viscusi, 2019](#); [Robinson et al., 2019](#)). By comparing these VSL estimates, we assess the assumption of linear preferences for mortality risk reduction. In theory, all calculated welfare measures should yield the same value, assuming no cost vector effects and scope sensitivity of preferences. Thus, any observed deviations challenge this assumption, shedding light on the behavioral and methodological factors influencing VSL estimates. Figure 1 visualizes the VSL estimates across cost vector groups, offering a clearer picture of the magnitude and pattern of differences than tabular presentation alone.

The point estimates of VSL vary substantially across cost vector treatments and scope scenarios, differing by up to 48% in absolute terms, ranging from a low of 762,240 PLN (LC $VSL_{\Delta Risk=3}$) to a high of 1,130,028 PLN (HC $VSL_{\Delta Risk=1}$). VSL estimates from HC treatment are consistently higher than those from LC treatment, by approximately 11% for $VSL_{\Delta Risk=1}$ and 12% for $VSL_{\Delta Risk=3}$. The pattern is less uniform when comparing LC and MC. While the LC $VSL_{\Delta Risk=1}$ estimate exceeds its MC counterpart by roughly 13%, the corresponding $VSL_{\Delta Risk=3}$ estimates are nearly identical across the two groups, diverging by less than 1%. The HC treatment yields the largest estimates overall, surpassing MC by approximately 25% for $VSL_{\Delta Risk=1}$ and 12% for $VSL_{\Delta Risk=3}$.

¹ Note that although the models include binary indicators for mortality risk reductions of two and four deaths per 1,000 (with a reduction of one death per 1,000 serving as a reference category), the marginal changes in risk used in VSL calculations are taken relative to this baseline. This follows directly from the interpretation of binary indicators, whose coefficients capture the effect of each category relative to the omitted reference level rather than in absolute terms. Specifically, the relevant increments are one (i.e., the difference between a reduction of two and the baseline reduction of one) and three (i.e., the difference between a reduction of four and the baseline reduction of one).

Table 4. Mixed logit results with correlated random parameters and derived VSL estimates for low cost, medium cost, and high cost treatment sub-samples

MXL model results						
	Low cost vector model (LC)		Medium cost vector model (MC)		High cost vector model (HC)	
Attributes	Mean (μ)	Standard Deviation (σ)	Mean (μ)	Standard Deviation (σ)	Mean (μ)	Standard Deviation (σ)
ASC (norm dist.)	4.45*** (0.45)	5.32*** (0.53)	4.27*** (0.42)	4.87*** (0.71)	4.95*** (0.52)	6.41*** (0.66)
Risk==2 (norm dist.)	1.97*** (0.17)	2.06*** (0.19)	1.71*** (0.17)	1.98*** (0.20)	1.51*** (0.17)	2.01*** (0.18)
Risk==4 (norm dist.)	4.72*** (0.36)	5.11*** (0.39)	4.39*** (0.37)	5.00*** (0.42)	3.34*** (0.30)	4.34*** (0.35)
Annual Cost/100 in PLN (log-norm dist.)	0.10 (0.14)	2.18*** (0.16)	-0.29** (0.15)	2.75*** (0.18)	-0.74*** (0.14)	2.60*** (0.20)
Model diagnostics						
LL at convergence	-2,468.26		-2,541.22		-2,607.84	
McFadden's pseudo-R ²	0.5491		0.5506		0.5512	
Ben-Akiva-Lerman's pseudo-R ²	0.6465		0.6521		0.6564	
AIC/n	0.9945		0.9835		0.9711	
BIC/n	1.0128		1.0012		0.9881	
n (observations)	4,992		5,196		5,400	
r (respondents)	416		433		450	
k (parameters)	14		14		14	
VSL estimates						
	Low cost vector (LC)		Medium cost vector (MC)		High cost vector (HC)	
VSL estimates	Mean (std. dev)	CI 2.5% CI 97.5%	Mean (std. dev)	CI 2.5% CI 97.5%	Mean (std. dev)	CI 2.5% CI 97.5%
$VSL_{\Delta Risk=1}$ (PLN)	1,021,993*** (165,791)	726,581 1,378,214	905,684*** (184,412)	578,997 1,297,386	1,130,028*** (267,752)	665,903 1,719,090
$VSL_{\Delta Risk=3}$ (PLN)	762,240*** (108,595)	571,776 995,184	762,871*** (133,090)	523,717 1,051,394	856,401*** (175,152)	549,631 1,236,756

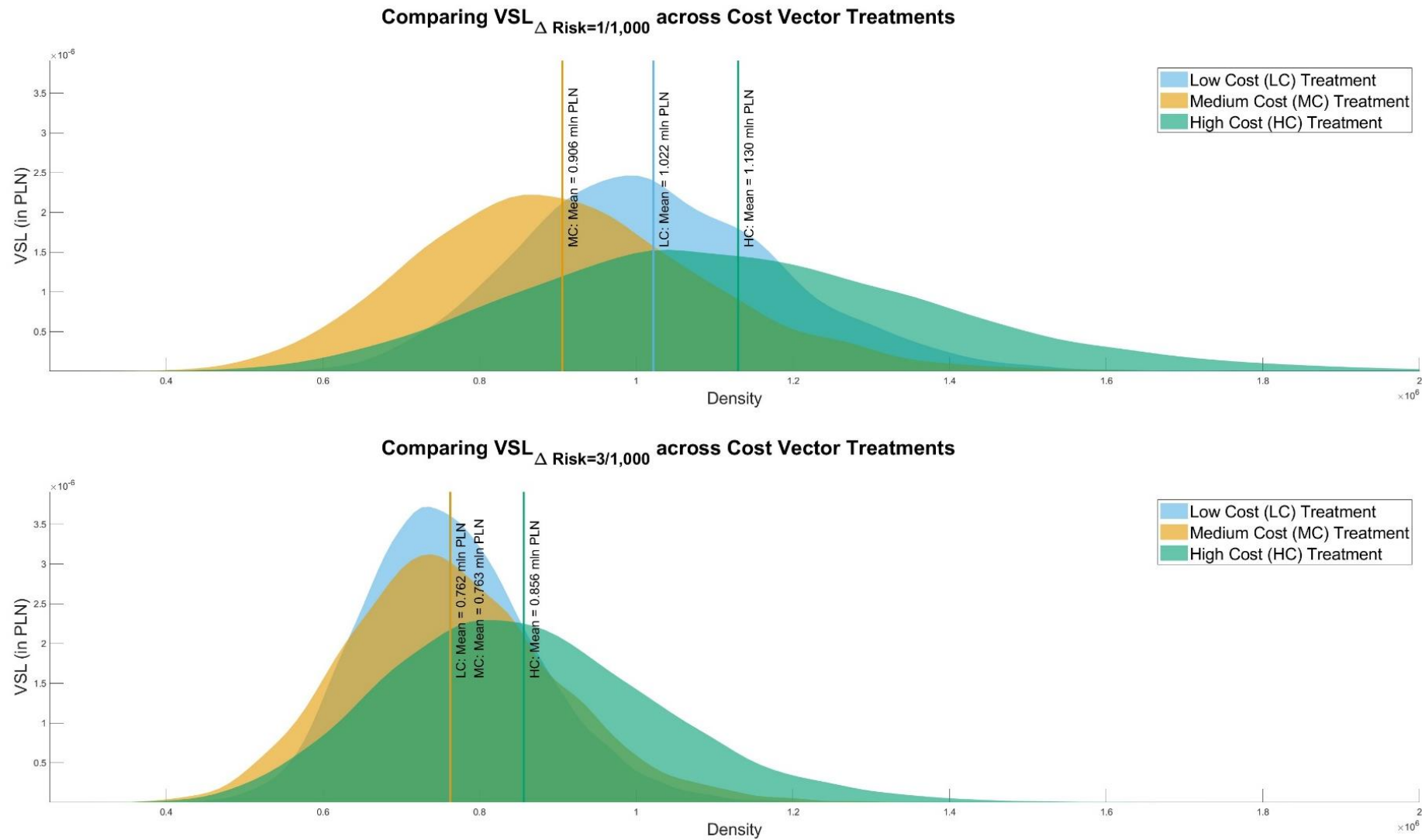
Notes: Significance levels: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$. $VSL_{\Delta Risk=1}$ indicates the value of statistical life based on the WTP for a mortality risk reduction from 1 to 2 per 1,000 people. $VSL_{\Delta Risk=3}$ is calculated for a reduction from 1 to 4 per 1,000. The confidence intervals were estimated using the Krinsky-Robb simulation procedure. Standard errors in parentheses.

A consistent within-treatment pattern also emerges with respect to scope sensitivity. Across all three models, the higher risk reduction scenario ($VSL_{\Delta Risk=3}$) yields a lower implied VSL than the lower risk reduction scenario ($VSL_{\Delta Risk=1}$), departing from the proportionality benchmark under which WTP is locally linear in risk reduction. The magnitude of this discrepancy is substantial, amounting to approximately 25% in both the LC and HC treatments, and 16% in the MC treatment.

To determine the statistical significance of these differences, the [Poe et al. \(2005\)](#) complete combinatorial test was applied to compare the Krinsky-Robb draws of the VSL. Each cost vector treatment is estimated using independent subsamples, so the test compares the sampling distributions of this estimator across treatments. It does not compare the population distributions of preferences and is not a test of stochastic dominance. The test computes the difference for every pair of draws from the two treatments. The two-sided p-value is twice the proportion of these differences that fall on the less frequent side of zero, so a small value indicates a significant difference in either direction. When comparing $VSL_{\Delta Risk=1}$ estimates across cost vectors, no significant differences were found between LC and MC (p-value = 0.64), LC and HC (p-value = 0.74), and MC and HC (p-value = 0.48). Similar results were observed for $VSL_{\Delta Risk=3}$ estimates, with a p-value of 0.99 for LC and MC, 0.66 for LC and HC, and 0.68 for MC and HC. These results suggest that while VSL estimates (calculated based on WTP for risk reduction of either one or three deaths) differed by up to 25%, the reported between-treatment contrasts were not statistically significant.

In contrast, internal scope sensitivity compares $VSL_{\Delta Risk=1}$ and $VSL_{\Delta Risk=3}$ within the same model, where the draws are correlated. For this comparison, we use the paired difference method ([Poe et al., 1997](#)), which takes the difference within each Krinsky-Robb draw and so preserves the covariance of the parameters. The p-value is computed from these differences in the same way. $VSL_{\Delta Risk=1}$ exceeds $VSL_{\Delta Risk=3}$ in all three treatments (p<0.001), indicating rejection of proportional WTP scaling over the tested increments within each cost vector. Whether WTP increases with risk reduction is a separate hypothesis.

Figure 1. Visual comparison of VSL estimates – density ridgeline plots



To further investigate the cost vector differences and better understand preference heterogeneity, we estimated an additional model incorporating various interactions (introduced as covariates of means), with the risk attribute encoded as a continuous attribute. The results are presented in Table 5 in the Appendix. The interactions for MC did not differ significantly from LC, whereas the HC interactions were significant for both the risk and the cost coefficient. Respondents assigned to the HC treatment expressed both a lower marginal utility of risk reduction and a smaller sensitivity to the cost attribute, of comparable magnitude. A lower marginal utility of risk reduction lowers WTP, whereas a smaller absolute cost coefficient raises it (see Equation 3). With changes of comparable size, the two effects largely offset each other. This is consistent with the 12% difference between the LC and HC VSL estimates reported above, which was not statistically significant. Nonetheless, significant shifts in both coefficients do not by themselves imply a significant shift in their ratio. Moreover, in a logit model, a proportional decline of both coefficients is also what a larger error variance, that is, a smaller scale, would produce. Taken together, these results indicate that the cost vector may affect choice behavior, through preferences, scale, or both, without a statistically detectable change in the reported VSL comparisons.

The results in Table 5 (Appendix) offer additional insights. Specifically, neither the disclosure of attributes (i.e., whether respondents were shown a preliminary screen detailing all attributes and levels) nor the inclusion of the lowest or highest cost vector element in the first choice task appeared to influence preferences. These null results do not establish that valuations are free of behavioral influences or reveal intrinsic preferences; they concern only the tested manipulations and the precision of our estimates.

In addition, a correct understanding of mortality risk reduction (assessed through three comprehension questions) was associated with differences in responses. However, this effect was comparable across respondents regardless of whether they had been exposed to the treatment providing feedback on the correct answer. This highlights that comprehension of risk reduction matters, while the feedback treatment produced no statistically detectable change in valuations. This does not establish that feedback cannot improve comprehension. This finding is of considerable importance. While it underscores that understanding of mortality risk shapes subsequent valuations, it also suggests that rapid learning during the course of the survey might not be sufficient to convey the concept of mortality risk to those who have not previously internalized it. Further research is nonetheless warranted, as it remains unclear whether respondents who answered the comprehension questions correctly did so because

of the explanations provided or because they already possessed sufficient prior knowledge before participating in the survey. This question, however, falls outside the scope of the present study, whose primary focus is on cost vector effects.

Beyond these findings, the model provides further insight into preference heterogeneity, illustrating how variations in sociodemographic characteristics, health status, and lifestyle factors shape the valuation of mortality risk reduction. For instance, despite the well-established higher mortality risk for cardiovascular diseases among males, no significant differences in preferences were observed between male and female respondents.

5. Discussion

5.1. Cost vector effects

SP methods have long been used to investigate WTP for health improvements ([Bridges, 2003](#); [Diener et al., 1998](#); [Klose, 1999](#); [Shiell & Gold, 2003](#)). In particular, DCEs play a critical role in valuing mortality risk reductions, despite ongoing debates concerning their reliability ([Doucouliagos et al., 2012](#); [Weinstein et al., 2001](#)). Point estimates of VSL differ by up to 25% across the tested cost vectors. Statistical tests, based on [Poe et al. \(2005\)](#), do not detect significant between-treatment differences. These comparisons concern uncertainty in the estimated summary measure, rather than equality of population preference distributions. They establish neither a detectable VSL treatment effect nor equivalence. However, because health policy practitioners often prioritize point estimates of marginal willingness to pay to inform decision-making, different point estimates should be interpreted alongside their uncertainty when evaluating policy decisions ([Chandoevrit & Wasi, 2020](#)).

It is therefore important to stress that the absence of statistically significant differences in the reported VSL comparisons across cost vector designs does not render the choice of cost vector inconsequential from a practical standpoint. Our findings show that the resulting WTP point estimates can diverge meaningfully, and it is precisely these estimates that feed into policy appraisals, cost-benefit analyses, and the setting of regulatory thresholds. A 25% difference between VSL point estimates could change a policy calculation, but its uncertainty prevents us from interpreting it as a measured distortion or a demonstrated behavioral effect.

The experiment varies the minimum, maximum, and spacing of the monetary vector jointly. It therefore cannot establish whether spacing alone causes the observed differences in point estimates or their precision. DCE responses are choices among alternatives, rather than

direct reports of WTP within cost brackets. Future studies should vary vector components independently and assess the resulting precision, credibility, and respondent burden.

5.2. Scope sensitivity

Scope sensitivity concerns whether WTP responds to the scale of the good or service being valued; proportionality is a stronger condition ([Carson, 1997](#); [Kahneman & Knetsch, 1992](#)). For small mortality risk changes, proportional WTP scaling is a useful local benchmark, but a departure from it does not by itself establish that WTP is insensitive to risk reduction or that preferences are inconsistent. Since VSL is premised on the idea that WTP should scale – at least weakly – with the size of the risk reduction, scope insensitivity can undermine the reliability of these estimates ([Andersson & Treich, 2011](#); [Bishop & Boyle, 2019](#)).

The literature provides diverse explanations for scope insensitivity. Cognitive constraints – such as difficulty conceptualizing small probability changes – are frequently cited ([Kahneman et al., 1999](#)). Respondents may also succumb to embedding effects, where they focus on the general idea of contributing to a “good cause” or “saving lives” and fail to distinguish among varying levels of the good ([Kahneman & Knetsch, 1992](#)). As a result, WTP responses can converge around a similar value regardless of the actual change in risk. Psychological factors like “warm glow” (i.e., the satisfaction of giving), taboo trade-offs ([Chorus et al., 2018](#); [Smeele et al., 2025](#)) and diminishing marginal utility for risk reductions may also contribute to non-proportional responses ([Chilton & Hutchinson, 2000](#); [Czajkowski & Hanley, 2009](#)).

Within health economics, understanding the scope sensitivity of VSL is critical. Less-than-proportional WTP scaling can affect the implied VSL used in policy appraisal. For instance, interventions that produce larger risk reductions could appear less cost-effective if WTP remains flat, while small interventions might be overvalued. Yet scope insensitivity might not arise in isolation – it can be systematically shaped by the structure of the cost attribute itself, in which case apparent insensitivity may reflect not a genuine cognitive limitation but an artifact of an insufficiently granular elicitation instrument. Consequently, addressing scope insensitivity requires careful experimental design, transparent presentation of risk changes, and, possibly, the inclusion of learning or feedback mechanisms to ensure respondents have adequate context for expressing coherent preferences.

Using proportionality as a local benchmark for small risk changes, the paired tests indicate less-than-proportional WTP scaling in all three cost-vector treatments. Specifically, we observe that respondents’ WTP for reducing mortality risk from one to four deaths per 1,000

is less than proportional when compared to smaller increments. These findings align with earlier literature that identifies difficulty among respondents in scaling willingness to pay for changes in small probabilities ([Andersson et al., 2016](#); [Kahneman & Knetsch, 1992](#)). Although the point estimates show positive scope sensitivity ([Goldberg & Roosen, 2007](#)) – WTP did rise for bigger risk reductions – the departure from proportionality warrants caution when transferring VSL estimates between risk magnitudes ([Carson, 1997](#); [Whitehead, 2016](#)).

Notably, however, this pattern of scope insensitivity was not confined to any single cost vector treatment but was instead evident across all three cost vector designs. This consistency shows that the pattern is present under each tested vector, but it does not identify its psychological cause or exclude features shared by all treatment arms. Cognitive explanations remain possible, rather than established ([Kahneman & Knetsch, 1992](#)).

5.3. *Anchoring*

Originally described by [Tversky and Kahneman \(1974\)](#), the anchoring effect posits that individuals exposed to an initial reference value – whether a price, statistic, or another numerical cue – tend to anchor subsequent judgments around that reference, even when it is arbitrary. In SP contexts, this phenomenon can lead to starting-point bias or reference-point dependence, where valuation responses are systematically influenced by numerical prompts that precede the main WTP questions ([Ariely et al., 2003](#); [Furnham & Boo, 2011](#)).

Anchoring is particularly relevant to studies using CV, where an initial bid in a dichotomous choice format may shape respondents' subsequent willingness to pay ([Boyle et al., 1985](#); [Flachaire & Hollard, 2007](#)). In double-bounded dichotomous choice settings, for instance, participants are first asked to accept or reject an initial bid, and then presented with a follow-up bid based on their response. The outcome of the first question can influence the second, potentially leading to systematically biased valuations – either overstated or understated ([Herriges & Shogren, 1996](#); [Onwujekwe & Nwagbo, 2002](#)).

In DCEs, anchoring can manifest through repeated choice tasks or instructional choice sets, which give respondents initial cost or attribute levels that shift how they perceive subsequent alternatives ([Ladenburg & Olsen, 2008](#); [Meyerhoff & Glenk, 2015](#)). Cost vector design can itself act as an anchor, as respondents may interpret higher cost levels as indicators of a more valuable or premium good, thus inflating WTP ([Carlsson & Martinsson, 2008](#); [Kragt, 2013](#)). Alternatively, if cost levels are set too low, participants might anchor on those amounts and discount the good's potential value.

Several theoretical explanations underscore why anchoring is so pervasive. The coherent arbitrariness hypothesis ([Ariely et al., 2003](#)) argues that consumers form preferences only once they are prompted to do so. In case of non-market goods (which are not traded in typical markets), respondents might thereby rely heavily on contextual cues – like initial cost bids – in constructing their valuations. Meanwhile, Bayesian updating approaches posit that participants may incorporate anchors as prior information, updating their “beliefs” in line with the anchor when knowledge about the good is otherwise limited ([Bateman et al., 2008](#); [Nguyen et al., 2015](#)).

While anchoring has been widely documented in SP literature, its influence is unlikely to operate in isolation. There is a compelling premise that anchoring may interact with other well-documented biases (such as scope insensitivity and cost vector effects), whereby the numerical cues embedded in cost vectors simultaneously anchor valuations and suppress sensitivity to the scale or scope of the good being valued. Disentangling these overlapping mechanisms is therefore central to designing SP surveys that capture genuine trade-offs.

While anchoring effects constitute a pervasive concern in SP studies ([Ariely et al., 2003](#); [Tversky & Kahneman, 1974](#)), we detect little evidence that varying the extremes of the cost vector or providing attribute disclosures affects respondents’ final valuations. Neither the inclusion of extremely high or low cost levels in the first choice set nor showing respondents all possible attribute levels in advance significantly influenced estimated preferences. This suggests that participants may rely more on other cues – such as their own health status or perceived baseline mortality risk – rather than latching onto extreme cost amounts as anchors, at least for the type of health-risk reductions considered here ([Krupnick et al., 2002](#)).

5.4. Limitations and further research avenues

While our findings offer valuable insights, the study also has certain limitations that point toward potential avenues for further research. First, we focused on a specific type of risk – mortality from cardiovascular diseases. Although this choice allowed for a more in-depth analysis of cost vector design and anchoring, future studies might explore broader health contexts or other risk factors to assess whether similar patterns hold.

Importantly, our study centers on a private good – namely, one’s own health – whereas the existing literature on cost vectors in DCEs has predominantly been developed in the context of public goods. This distinction carries meaningful implications. In public goods literature, considerable attention has been devoted to issues of consequentiality and incentive

compatibility, with researchers developing tailored scripts designed to encourage respondents to treat their stated preferences as consequential and to respond as they would in real-world decision-making contexts ([Carson & Groves, 2007](#); [Vossler et al., 2012](#); [Vossler et al., 2025](#); [Welling et al., 2022](#)). We adopted a similar approach here, incorporating such scripts to prompt respondents to reflect carefully on their valuations and to answer as though facing genuine health-related trade-offs. It is plausible, therefore, that this framing partially mitigated the behavioral biases that might otherwise distort responses in a public good context. On the contrary, the moral nature of the valued good could incur taboo trade-offs, whereby some respondents could find it ethically uncomfortable or psychologically difficult to place a monetary value on their own life and health, potentially rendering them unable or unwilling to engage meaningfully with the valuation task ([Chorus et al., 2018](#); [Smeele et al., 2025](#)). Whether this mitigation was more or less effective in a private good setting compared to public good contexts remains an open and empirically important question, and one that future research would do well to address.

Second, the three vectors change range and spacing jointly, so we cannot identify their separate effects, nor did we incorporate morbidity attributes – an aspect that can influence the valuation of health interventions ([Gentry & Viscusi, 2016](#)). Future research might extend this work by incorporating morbidity risk or additional attributes to capture a more comprehensive view of health outcomes, while simultaneously examining how differently structured cost vectors interact with increased attribute complexity.

Beyond simply enriching the DCE, the inclusion of additional attributes may have substantive implications for the very behavioral phenomena examined in this study. In our design, respondents were presented with a single non-cost attribute, which may have made it comparatively straightforward to form a coherent internal valuation and maintain consistency across repeated choice tasks. With only one attribute to consider alongside cost, the cognitive burden could remain relatively manageable, potentially allowing respondents to engage more deliberately and anchor their responses to genuinely considered preferences. Conversely, as the number of attributes increases, respondents may become overwhelmed by the volume of information and the multiplicity of trade-offs they are asked to process simultaneously. Under such conditions of cognitive overload, individuals may be more likely to resort to heuristics or simplifying strategies, thereby becoming more susceptible to behavioral biases such as anchoring. It follows that the effects of cost vector designs documented in our study may be amplified in richer choice environments.

Third, our design did not employ pivot-based approaches, which can tailor cost levels to each respondent's baseline conditions, potentially reducing irrelevant variation in cost vectors ([Hess & Rose, 2009](#); [Rose & Hess, 2009](#)). Investigating whether pivot designs mitigate the scope insensitivity observed here is a logical next step. This consideration is particularly salient in the context of health valuation, where preference heterogeneity among respondents is likely to be substantial. Individuals differ in their circumstances, risk attitudes, income levels, and personal experience with illness, all of which can give rise to wide variation in WTP for health risk reductions. While some respondents may hold relatively modest WTP values, others may be willing to pay considerably more, meaning that a single, uniform cost vector is unlikely to be equally relevant or meaningful across the full spectrum of the sample (unless it consists of many more elements, which, in turn, necessitates a much bigger sample size). This heterogeneity is directly interlinked with the challenge of cost vector selection with a range that is appropriately calibrated for respondents with various WTP magnitudes. A pivot-based design, by anchoring levels to each respondent's individual baseline (such as their current expenditures, stated budget constraints, or personal valuation), could help address this issue if the presented cost range remains personally relevant and economically plausible for each participant. In doing so, pivot approaches may not only reduce the noise introduced by ill-fitting cost vectors but also help disentangle genuine preference heterogeneity from artifacts of poor cost vector calibration, thereby yielding more reliable and individually meaningful WTP estimates.

Finally, we focused on conventional presentation formats for small probability changes, but growing evidence suggests that re-expressing these as percentages or using visual cues may further improve comprehension ([Corso et al., 2001](#); [Herrera-Araujo et al., 2022](#); [Marceta et al., 2025](#)). Implementing such strategies – and systematically comparing them to more traditional formats – could offer further insights into how individuals process small but critical shifts in health risks.

5.5. Contemporary recommendations for discrete choice experiments

The scope results and variation in VSL point estimates motivate transparent reporting of monetary-vector construction and estimation uncertainty. Our experiment does not establish that finer spacing improves valuation accuracy, because range and spacing change jointly. The following considerations draw on general design principles and identify questions for further research; their effectiveness is not demonstrated by this experiment.

Second, feedback mechanisms, such as informing participants of correct or incorrect responses to risk-comprehension tests, did not produce statistically significant changes in valuations in our sample. Although providing feedback can help maintain engagement and clarify complex probabilities, it appears that it may not drastically alter WTP estimates in health contexts like ours. Nevertheless, carefully implemented comprehension checks remain advisable as a means of ensuring that respondents understand the nature of the good being valued.

Third, while framing and anchoring are well-known concerns, our study finds that disclosing attribute levels upfront or including extreme cost values in the initial choice set did not produce statistically significant changes in the reported valuations. This outcome may reflect the intrinsic salience of health issues: respondents might rely on personal experiences and risk perceptions rather than purely external numeric cues. It would therefore be premature to conclude that anchoring poses no risk in other, less salient contexts. Researchers should continue to randomize the presentation of attribute information and test for anchoring effects where possible.

In practical terms, practitioners designing SP studies for valuing health risks can consider the following design and reporting choices:

1. **Justify cost support using pilot evidence and plausible payment amounts.**
Report acceptance at the highest cost instead of assuming that demand has been choked off.
2. **Justify spacing as well as range, and assess precision and respondent burden.**
The present experiment does not identify an optimal spacing rule or establish that finer increments improve accuracy.
3. **Include comprehension checks** – this helps confirm that respondents understand key elements (e.g., the probability changes), but do not assume that feedback alone will correct biases.
4. **Test for scope sensitivity explicitly** – present multiple magnitudes of risk reduction and distinguish tests of positive WTP responses from tests of proportional scaling. Use follow-up checks or alternative elicitation formats to ensure respondents grasp small probability changes.
5. **Evaluate anchoring risks** – randomize the order in which cost levels or attributes are introduced, and, where feasible, compare sub-samples exposed to different framing strategies.

These considerations can help assess design sensitivity and communicate uncertainty. Our study does not establish that they eliminate cost-vector effects, anchoring, or departures from proportional WTP scaling. Testing their effectiveness remains a task for future research.

6. Conclusions

This study investigated the robustness of VSL estimates derived from SP methods – particularly DCEs – in the context of cardiovascular disease mortality risk reductions. By systematically varying cost vectors, examining potential anchoring effects, and testing for scope sensitivity, we shed new light on how survey design factors and cognitive biases may shape respondents' WTP.

Point estimates of VSL differ by up to 25% across low, medium, and high cost vectors, but the reported comparisons are not statistically significant. The tests concern the sampling uncertainty of the estimated VSL summary measure. They do not demonstrate equality of population preference distributions or equivalence between treatments. For policy appraisal, point estimates and their uncertainty should therefore be reported together.

Other design factors proved less consequential. Neither upfront disclosure of attribute levels, the presence of the lowest or highest cost element in the first choice task, nor feedback about risk mortality comprehension significantly altered participants' preferences. These null results apply to the tested manipulations and do not establish that valuations are stable or free of bias.

Scope insensitivity, however, remains a more fundamental challenge. In our study, respondents did not consistently scale their WTP in proportion to increasing risk reductions, and – crucially – this insensitivity was not isolated to any particular cost vector treatment but emerged consistently across all of them. This identifies a common empirical pattern across the tested vectors, but does not distinguish cognitive mechanisms from features shared by the treatment arms.

From a broader perspective, this study underscores two distinct lessons for health risk valuation. First, cost vector effects should be treated as a first-order methodological decision rather than a technical detail. Different VSL point estimates may change a policy calculation, so their uncertainty should accompany any comparison. Second, departures from proportional WTP scaling warrant further investigation; they do not by themselves show that WTP is unresponsive to risk magnitude.

In sum, our analysis underscores the pressing need for standardized guidelines on cost vector selection, sustained attention to scope sensitivity, and continued innovation in survey design. Refining these methods is essential if VSL estimates are to provide robust foundations for valuing life-saving health interventions and, ultimately, for the policy decisions that depend on them.

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Appendices

Table 5. Mixed logit model with correlated random parameters in preference-space with covariates of means

Main effects					
Main effects		Not SQ (norm. dist.)		Risk (norm dist.)	Annual Cost/100 in PLN (log-norm dist.)
Mean (μ)		-0.74 (1.53)		1.59*** (0.38)	-1.71*** (0.49)
Standard Deviation (σ)		5.38*** (0.31)		1.36*** (0.07)	2.09*** (0.10)
Interactions (Covariates of mean)					
Interactions (Covariates of mean)		Not SQ (norm. dist.)		Risk (norm dist.)	Annual Cost/100 in PLN (log-norm dist.)
Medium cost vector in DCE (bsl: Low cost vector in DCE)		-0.40 (0.55)		-0.09 (0.14)	-0.11 (0.14)
High cost vector in DCE (bsl: Low cost vector in DCE)		0.38 (0.63)		-0.32** (0.14)	-0.35* (0.19)
No disclosure of attributes (bsl: Disclosure of attributes)		0.73 (0.46)		0.16 (0.11)	0.12 (0.12)
Only the lowest cost in 1st CS (bsl: Not facing both the lowest and the highest elements of the cost vector in the first choice task)		0.15 (0.63)		0.15 (0.15)	-0.09 (0.14)
Only the highest cost in 1st CS (bsl: Not facing both the lowest and the highest elements of the cost vector in the first choice task)		0.78 (0.58)		0.12 (0.14)	0.07 (0.16)
The lowest and highest cost in the 1st CS (bsl: Not facing both the lowest and the highest elements of the cost vector in the first choice task)		0.94 (0.69)		0.24 (0.17)	0.13 (0.24)
Information on correct answer X Incomplete comprehension 2/3 (bsl: Answering correctly three comprehension questions when getting informed about the correct answer)		1.73** (0.86)		-0.47** (0.20)	- 0.47*** (0.18)
Information on correct answer X Incomplete comprehension 1/3 (bsl: Answering correctly three comprehension questions when getting informed about the correct answer)		1.50* (0.88)		-1.12*** (0.21)	- 1.18*** (0.29)
Information on correct answer X Incomplete comprehension 0/3 (bsl: Answering correctly three comprehension questions when getting informed about the correct answer)		0.03 (0.83)		-1.48*** (0.20)	- 1.96*** (0.25)
No information on correct answer X Incomplete comprehension 2/3 (bsl: Answering correctly three comprehension questions without getting informed about the correct answer)		-0.35 (0.80)	-0.78*** (0.20)	-0.52** (0.25)	
No information on correct answer X Incomplete comprehension 1/3 (bsl: Answering correctly three comprehension questions without getting informed about the correct answer)		1.05 (0.92)	-1.00*** (0.21)	-2.05*** (0.24)	
No information on correct answer X Incomplete comprehension 0/3 (bsl: Answering correctly three comprehension questions without getting informed about the correct answer)		0.81 (0.83)	-1.33*** (0.20)	-1.91*** (0.26)	
Male (bsl: Female)		-0.62 (0.49)		-0.19 (0.12)	-0.02 (0.13)
Age 25-44 (bsl: age 18-24)		0.04 (0.79)		-0.08 (0.19)	0.38* (0.22)
Age 45-64 (bsl: age 18-24)		-0.64 (0.87)		-0.14 (0.21)	0.47* (0.25)
Age 65+ (bsl: age 18-24)	-2.57** (1.00)	0.08 (0.25)	-0.39* (0.22)		
Lower Secondary Education or lower (bsl: Basic Vocational Education or Secondary and Post-secondary Non-tertiary Education)		0.15 (1.61)		0.01 (0.37)	0.75** (0.35)

Higher education (bsl: Basic Vocational Education or Secondary and Post-secondary Non-tertiary Education)	-0.02 (0.53)	0.24* (0.12)	0.17 (0.17)
Countryside (bsl: living in the city up to 500k residents)	-0.63 (0.55)	-0.03 (0.13)	-0.14 (0.16)
Big city 500k+ (bsl: living in the city up to 500k residents)	-0.65 (0.63)	0.35** (0.16)	0.40*** (0.12)
House hold size==1 (bsl: house hold size >=3)	1.42* (0.80)	-0.19 (0.19)	0.43** (0.17)
HH==2 (bsl: house hold size >=3)	0.99* (0.55)	0.11 (0.13)	-0.02 (0.13)
EQ5D5L HUS <0.8.0.9 (bsl: health utility score >=0.9 perfect health)	0.31 (0.76)	0.12 (0.18)	0.44*** (0.16)
EQ5D5L <0.8 (bsl: health utility score >=0.9 perfect health)	-1.00 (0.79)	-0.33* (0.20)	-0.48* (0.26)
No doctor appointments (bsl: at least once a year, but no more frequent than once every two weeks)	-0.82 (1.35)	-0.04 (0.32)	0.70* (0.43)
Frequent doctor appointments (bsl: at least once a year, but no more frequent than once every two weeks)	3.12 (1.96)	0.18 (0.44)	-0.03 (0.38)
No alcohol consumption (bsl: at least once a year, but no more frequent than once every two weeks)	0.20 (0.63)	-0.13 (0.16)	0.53*** (0.18)
Frequent alcohol consumption (bsl: at least once a year, but no more frequent than once every two weeks)	0.76 (0.59)	0.13 (0.15)	0.74*** (0.16)
No smoking (bsl: at least once a year, but no more frequent than once every two weeks)	-0.95 (0.89)	0.18 (0.22)	0.14 (0.23)
Frequent smoking (bsl: at least once a year, but no more frequent than once every two weeks)	0.19 (0.93)	0.28 (0.23)	0.24 (0.21)
No drugs (bsl: at least once a year, but no more frequent than once every two weeks)	2.77** (1.15)	-0.03 (0.29)	0.87*** (0.32)
Frequent drug use (bsl: at least once a year, but no more frequent than once every two weeks)	2.88 (2.33)	0.18 (0.55)	-0.89* (0.50)
0 min of activity (bsl: 1-300 min of physical activity per week)	-0.94 (0.84)	0.29 (0.21)	0.81*** (0.24)
300 min+ of activity (bsl: 1-300 min of physical activity per week)	-0.95 (0.72)	0.27 (0.20)	0.39** (0.17)
BMI (25.35> (bsl: BMI under 25; underweight)	0.58 (0.65)	-0.16 (0.16)	-0.08 (0.13)
BMI 35+ (bsl: BMI under 25; underweight)	0.73 (0.80)	-0.04 (0.18)	0.27 (0.16)
Chronic diseases (bsl: not having any chronic diseases)	0.73 (0.50)	-0.02 (0.12)	0.00 (0.16)
Cardiovascular diseases (bsl: not having any cardiovascular diseases)	-0.02 (0.63)	0.09 (0.15)	-0.34** (0.15)
Cardiovascular diseases in family (bsl: not having any cardiovascular diseases in family)	1.71*** (0.49)	0.17 (0.12)	0.36*** (0.12)
Risk perception – lower (bsl: stating that risk perception is the same as average in population)	0.55 (0.56)	-0.07 (0.13)	0.49*** (0.12)
Risk perception – higher (bsl: stating that risk perception is the same as average in population)	-1.46* (0.86)	0.35 (0.23)	0.04 (0.22)
Risk perception - I don't know (bsl: stating that risk perception is the same as average in population)	-0.54 (0.74)	-0.59*** (0.17)	0.59** (0.24)
Income >10k PLN/month (bsl: income <10k PLN/month)	-1.23** (0.60)	0.10 (0.15)	-0.59*** (0.13)

Model diagnostics	
LL at convergence	-7,443.45
McFadden's pseudo-R ²	0.5633
Ben-Akiva-Lerman's pseudo-R ²	0.6585
AIC/n	0.9727
BIC/n	1.0405
n (observations)	15,588
r (respondents)	1,299
k (parameters)	138

*Note: *** for p -value < 0.01, ** for p -value < 0.05, * for p -value < 0.1. The EQ-5D-5L utility tariffs were calculated using the value set derived by [Golicki et al. \(2019\)](#). bsl – baseline level.*

Questionnaire

New screen

This study is carried out as part of research conducted by the University of Warsaw. It concerns the valuation of health and willingness to pay for reducing the risk of mortality from cardiovascular diseases.

Your answers matter! The results of this survey will be presented to local, national, and European authorities and may influence future regulations and health policies (among other things, they may serve as decision aids vis-à-vis various health interventions or resource allocation).

All your responses are anonymous and will remain confidential - we will only use and present the results in aggregate form.

It takes about 20 minutes to complete the survey. Thank you for participating in the survey!

A: Sociodemographic questions

New screen

To begin with, we would like to ask some questions about you and your household. This information will allow us to assess how representative the group of respondents taking part in the survey is.

#Q1. What is your gender:

- 1 Woman
- 2 Male
- 3 Other/Deny answer

New screen

#Q2. What is your year of birth? (enter number)

__ __ __ __ (Range check: 1900-2006)

New screen

#Q3. What education do you have?

- 1 Incomplete Primary or No School Education
- 2 Completed Primary Education
- 3 Lower Secondary Education
- 4 Basic Vocational Education
- 5 Secondary or Post-secondary Non-tertiary Education
- 6 Higher Education

New screen**#Q4.** What is the size of the town where you live?

- 1 Village/Countryside
- 2 City up to 50,000 inhabitants
- 3 City of 50,000 to 100,000 inhabitants
- 4 City of 100,000 to 500,000 inhabitants
- 5 City with more than 500,000 inhabitants

New screen**#Q5.** What province do you live in?

- 1 dolnośląskie
- 2 kujawsko-pomorskie
- 3 lubelskie
- 4 lubuskie
- 5 łódzkie
- 6 małopolskie
- 7 mazowieckie
- 8 opolskie
- 9 podkarpackie
- 10 podlaskie
- 11 pomorskie
- 12 śląskie
- 13 Świętokrzyskie
- 14 warmińsko-mazurskie
- 15 wielkopolskie
- 16 zachodniopomorskie

New screen**#Q6.** How many people (including yourself) live in your household? (A household is people living under one roof and sharing a common budget.)

___ __ people

New screen**#Q7.** What is your household's total net monthly income (take-home pay)? Please include all sources of income - including wages, pensions, social benefits, scholarships, rental income, etc.

- 1 < 1,000 PLN
- 2 PLN 1,000 - PLN 1,999
- 3 PLN 2,000 - PLN 2,999

- 4 PLN 3,000 - PLN 3,999
- 5 PLN 4,000 - PLN 4,999
- 6 PLN 5,000 - PLN 7,499
- 7 PLN 7,500 - PLN 9,999
- 8 PLN 10,000 - PLN 12,499
- 9 PLN 12,500 - PLN 14,999
- 10 PLN 15,000 - PLN 17,499
- 11 PLN 17,500 - PLN 19,999
- 12 > 20,000 PLN
- 13 Refusal to answer

New screen

#Q8. What is the total net monthly income (take-home pay) of your household? Please include all sources of income - including wages, pensions, social benefits, scholarships, rental income, etc.

___ ___ ___ PLN

☐ Refusal to answer

B: Current health (E5-5D-5L)**New screen**

To begin with, we would like to know your current health status. At this point, we would like to emphasize again that all answers provided are anonymous and will be kept confidential - we will use and present the results only in the form of summary statements.

New screen

Information at the top of the card: EQ-5D-5L

Information at the bottom of the card: © EuroQol Research Foundation. EQ-5D™ is a trade mark of the EuroQol Research Foundation. Poland (Polish) v1.0

Non-response information: No answer, please complete.

Health Questionnaire.
Polish version for use in Poland
(Polish version for Poland)

Under each heading, please tick the **ONE** box that best describes your health **TODAY**

#Q9. MOBILITY

- 1 I have no problems in walking about
- 2 I have slight problems in walking about
- 3 I have moderate problems in walking about
- 4 I have severe problems in walking about
- 5 I am unable to walk about

#Q10. SELF-CARE

- 1 I have no problems washing or dressing myself
- 2 I have slight problems washing or dressing myself
- 3 I have moderate problems washing or dressing myself
- 4 I have severe problems washing or dressing myself
- 5 I am unable to wash or dress myself

#Q11. USUAL ACTIVITIES (e.g. work, study, housework, family or leisure activities)

- 1 I have no problems doing my usual activities
- 2 I have slight problems doing my usual activities
- 3 I have moderate problems doing my usual activities
- 4 I have severe problems doing my usual activities
- 5 I am unable to do my usual activities

#Q12. PAIN / DISCOMFORT

- 1 I have no pain or discomfort
- 2 I have slight pain or discomfort
- 3 I have moderate pain or discomfort
- 4 I have severe pain or discomfort
- 5 I have extreme pain or discomfort

#Q13. ANXIETY / DEPRESSION

- 1 I am not anxious or depressed
- 2 I am a slightly anxious or depressed
- 3 I am moderately anxious or depressed
- 4 I am severely anxious or depressed
- 5 I am extremely anxious or depressed

New screen



Information at the top of the card: EQ-5D-5L

Information at the bottom of the card: © EuroQol Research Foundation. EQ-5D™ is a trade mark of the EuroQol Research Foundation. Poland (Polish) v1.0

Option to go to the previous question: Previous/Next

Non-response information: No answer, please complete.

#Q14. We would like to know how good or bad your health is TODAY. This scale is numbered from 0 to 100.

100 means the best health you can imagine.

0 means the worst health you can imagine.

Please mark an X on the scale to indicate how your health is TODAY.

Thermometer: 'Health today' from 0 ('Worst health imaginable') to 100 ('Best health imaginable').

YOUR HEALTH TODAY = The value from the scale.

C: Current health

New screen

#Q15. How often do you go to the doctor?

- 1 Never
- 2 Less than once a year
- 3 Once a year
- 4 Every few months
- 5 Once a month
- 6 Once every two weeks
- 7 Once a week
- 8 Several times a week
- 9 Everyday
- 10 I refuse to answer

New screen

#Q16. Do you have (or have you had in the past) any chronic diseases?

The most common chronic diseases include autoimmune diseases (e.g. rheumatoid arthritis, multiple sclerosis, celiac disease, lupus erythematosus, Hashimoto's or Crohn's disease), cerebrovascular diseases, cardiovascular diseases (e.g. arrhythmia, atrial fibrillation, hypertension, atherosclerosis or heart failure), diabetes, HIV/AIDS infection, cancer, osteoporosis, obesity, epilepsy and chronic respiratory diseases (e.g., asthma or COPD - chronic obstructive pulmonary disease).

- 1 Yes
 - a. Which ones? (Q16A) _____
- 2 No
- 3 I don't know
- 4 I refuse to answer

New screen

#Q17. Do you have (or have you had in the past) any cardiovascular diseases?

Cardiovascular diseases are diseases of the heart and blood vessels. The most common cardiovascular diseases are hypertension, peripheral artery disease (such as atherosclerosis), myocardial infarction, stroke, heart failure, and coronary artery disease.

Other diseases include arrhythmia, rheumatic heart disease, valvular heart disease, cardiomyopathy, aortic aneurysm, congenital heart defects, deep vein thrombosis, myocarditis, pericarditis, endocarditis, and pulmonary embolism.

- 1 Yes
 - a. Which ones?
 - Arrhythmia (Q17A_1)
 - Rheumatic heart disease (Q17A_2)
 - Peripheral artery disease (e.g., atherosclerosis) (Q17A_3)
 - Coronary artery disease (Q17A_4)
 - Valvular heart disease (Q17A_5)
 - Cardiomyopathy (Q17A_6)
 - Hypertension (Q17A_7)
 - Heart failure (Q17A_8)
 - Aortic aneurysm (Q17A_9)
 - Stroke (Q17A_10)
 - Congenital heart defects (Q17A_11)
 - Deep vein thrombosis (Q17A_12)
 - Myocarditis (Q17A_13)
 - Pericarditis (Q17A_14)
 - Endocarditis (Q17A_15)
 - Pulmonary embolism (Q17A_16)

- Myocardial infarction (Q17A_17)
 - Other, please specify which? _____ (Q17A_18)
- 2 No
- 3 I don't know
- 4 I refuse to answer

New screen

#Q18. Does anyone in your biological family (family related by blood ties) have (or have had in the past) any cardiovascular disease?

Cardiovascular diseases are diseases of the heart and blood vessels. The most common cardiovascular diseases are hypertension, peripheral artery disease (such as atherosclerosis), myocardial infarction, stroke, heart failure and coronary artery disease.

Other diseases include arrhythmia, rheumatic heart disease, valvular heart disease, cardiomyopathy, aortic aneurysm, congenital heart defects, deep vein thrombosis, myocarditis, pericarditis, endocarditis and pulmonary embolism.

- 1 Yes
- a. Which ones?
- Arrhythmia (Q18A_1)
 - Rheumatic heart disease (Q18A_2)
 - Peripheral artery disease (e.g., atherosclerosis) (Q18A_3)
 - Coronary artery disease (Q18A_4)
 - Valvular heart disease (Q18A_5)
 - Cardiomyopathy (Q18A_6)
 - Hypertension (Q18A_7)
 - Heart failure (Q18A_8)
 - Aortic aneurysm (Q18A_9)
 - Stroke (Q18A_10)
 - Congenital heart defects (Q18A_11)
 - Deep vein thrombosis (Q18A_12)
 - Myocarditis (Q18A_13)
 - Pericarditis (Q18A_14)
 - Endocarditis (Q18A_15)
 - Pulmonary embolism (Q18A_16)
 - Myocardial infarction (Q18A_17)
 - Other, please specify which? _____ (Q18A_18)
- 2 No
- 3 I don't know
- 4 I refuse to answer

New screen**#Q19.** How often do you consume alcohol?

- 1 Never
- 2 Less than once a year
- 3 Once a year
- 4 Every few months
- 5 Once a month
- 6 Once every two weeks
- 7 Once a week
- 8 Several times a week
- 9 Everyday
- 10 I refuse to answer

New screen**If 2<Q19<9****#Q19A.** On a scale of 1 to 10, how highly would you rate the intensity of your alcohol consumption?

- 1 - drinking small amounts
10 - drinking to the extreme

New screen**#Q20.** How often do you smoke tobacco products (such as cigarettes or cigars) or nicotine products (such as e-cigarettes)?

- 1 Never
- 2 Less than once a year
- 3 Once a year
- 4 Every few months
- 5 Once a month
- 6 Once every two weeks
- 7 Once a week
- 8 Several times a week
- 9 Everyday
- 10 I refuse to answer

New screen**#Q21.** How often do you use drugs, legal highs, or drugs that have intoxicating properties?

- 1 Never
- 2 Less than once a year

- 3 Once a year
- 4 Every few months
- 5 Once a month
- 6 Once every two weeks
- 7 Once a week
- 8 Several times a week
- 9 Everyday
- 10 I refuse to answer

New screen**#Q22.** How often do you engage in physical activities?

- 1 Never
- 2 Less than once a year
- 3 Once a year
- 4 Every few months
- 5 Once a month
- 6 Once every two weeks
- 7 Once a week
- 8 Several times a week
- 9 Everyday
- 10 I refuse to answer

New screen**#Q23.** How many minutes per week do you spend on physical activities?

___ ___ ___ min

☐ Refusal to answer**New screen****#Q24.** What is your current weight?

___ ___ ___ kg.

☐ Refusal to answer**New screen****#Q25.** What is your current height?

___ ___ ___ cm.

☐ Refusal to answer

D: Cardiovascular diseases description

New screen

This part of the survey will present information about cardiovascular diseases and the associated mortality risk. This information is intended to give an overview of the problem under study and to facilitate health valuation decisions later in the survey.

Cardiovascular diseases are diseases of the heart and blood vessels. The most common cardiovascular diseases are hypertension, peripheral artery disease (such as atherosclerosis), myocardial infarction, stroke, heart failure, and coronary artery disease.

Other examples of cardiovascular diseases include arrhythmia, rheumatic heart disease, valvular heart disease, cardiomyopathy, aortic aneurysm, congenital heart defects, deep vein thrombosis, myocarditis, pericarditis, endocarditis, and pulmonary embolism.

Cardiovascular diseases are the most common cause of death in Poland. In 2021, they accounted for **35% of all deaths** in Poland (around 180 thousand deaths). In comparison, the second consecutive cause of death was cancer (19% - 97 thousand deaths). It is worth noting that these values refer only to the leading causes of death (they do not take into account cases of a combination of various comorbidities).

Many factors can be the cause of diseases of the circulatory system, including inadequate diet and too little physical activity. They can be treated, limiting their progress and reducing the risk of complications. An essential part of prevention is changing lifestyles and getting rid of harmful habits.

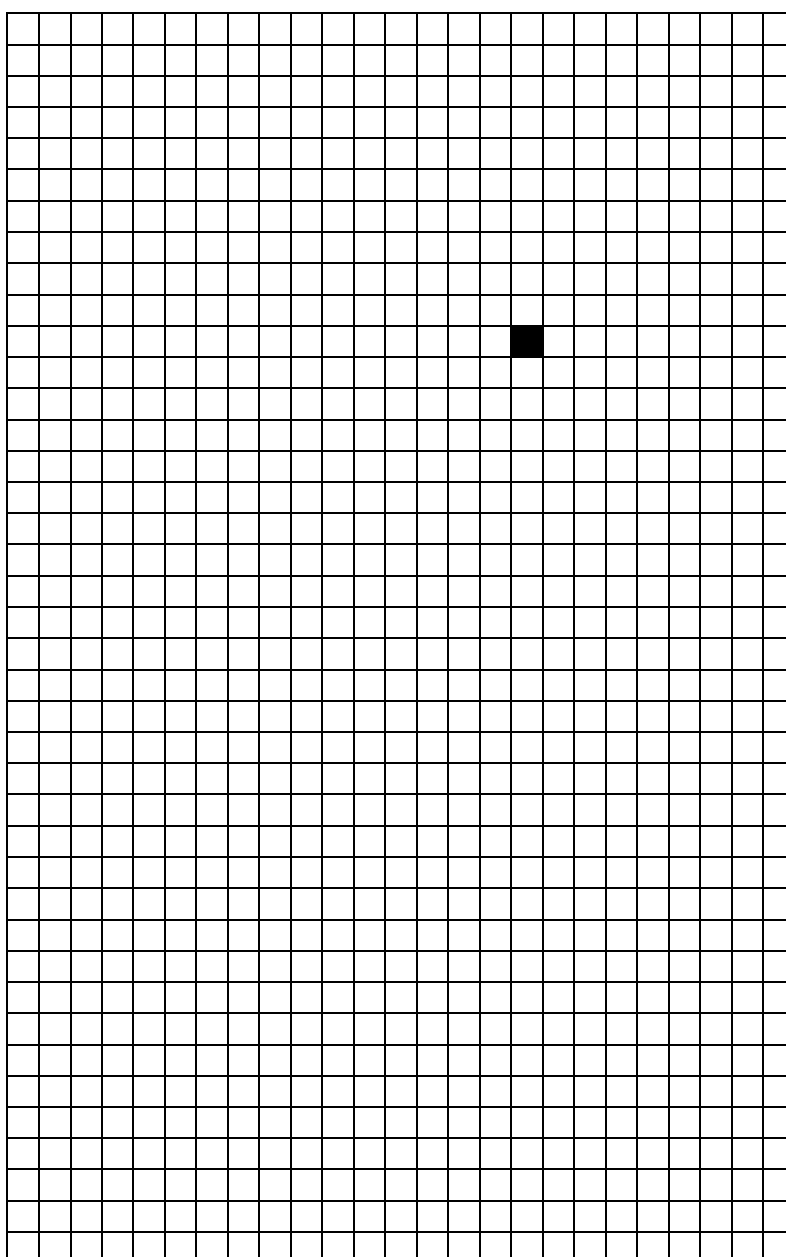
A number of factors contribute to the onset of cardiovascular disease. People who have several of them at the same time are most at risk:

- overweight,
- obesity,
- lack of physical activity,
- inadequate diet,
- addiction to smoking (including tobacco/nicotine products),
- excessive alcohol consumption,
- excessive energy drink consumption,
- high cholesterol (or triglycerides),
- poor glucose tolerance (diabetes or insulin resistance),
- age (older patients are more prone to the disease),
- high amount of stress,
- depressive states (depression or mood lows),
- gender (men are more likely to suffer from the disease),
- genetic factors (the presence of such diseases in the family).

E: Mortality risk reduction and life expectancy extension**New screen**

This part of the survey concerns the mortality risk. This risk can be expressed as the number of deaths per 1,000 people in a given period (e.g., per 10 years). In the table below, a single square represents one person (1,000 squares in each table represent 1,000 people). The black box represents a single death (in the case of this study, caused by cardiovascular diseases), while the white boxes represent survivors.

This table shows 1 person out of 1,000 who will die in the next 10 years. This means that 999 people out of 1,000 will survive. In other words, we can say that the risk of dying in the next 10 years is equal to 1 in 1000.

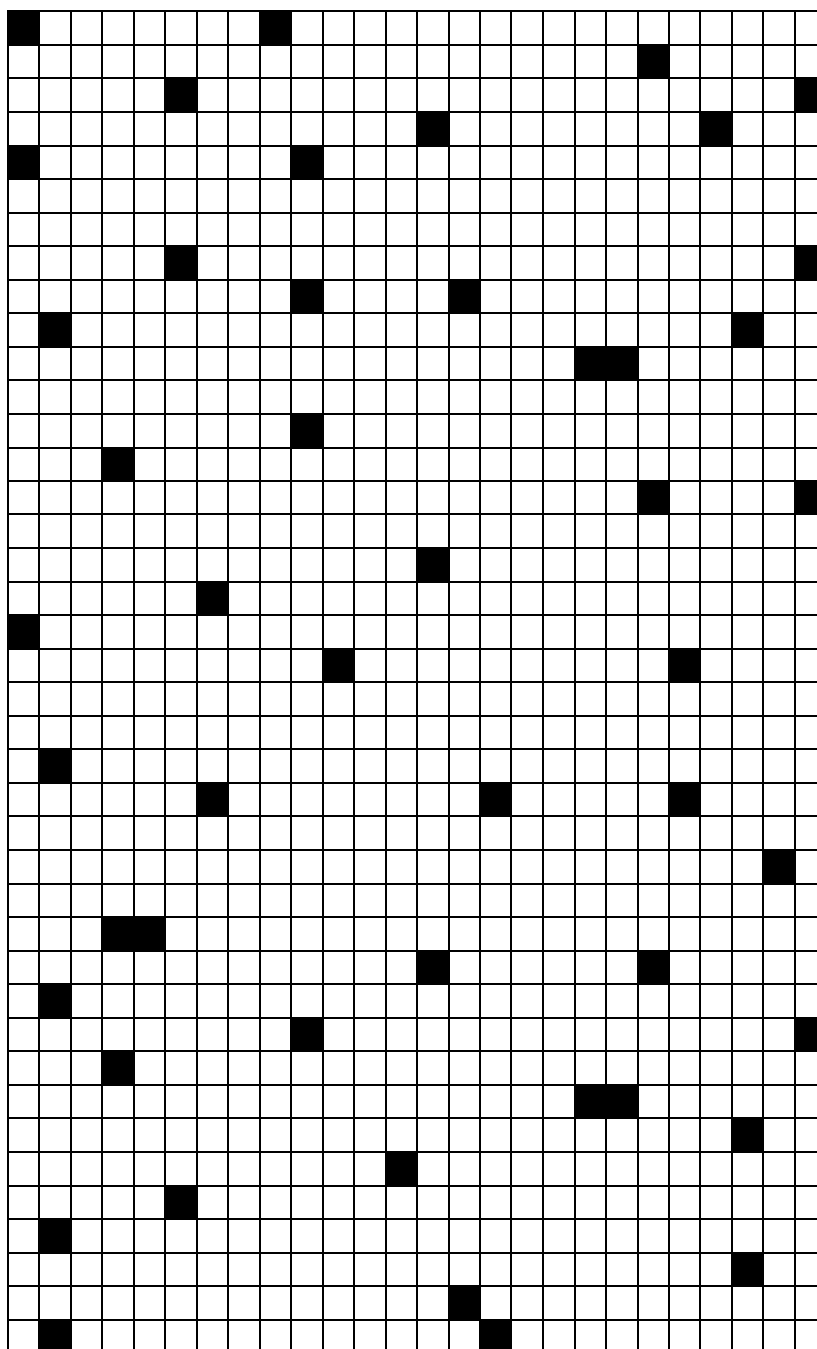


To better understand the problem under study, you can imagine that you are one of a thousand squares (a thousand people of similar age and gender).

New screen

In Poland, the average mortality risk from cardiovascular disease is 47 per 1,000 people over the next 10 years.

The table below shows 47 people out of 1,000 who will die in the next 10 years. In other words, we can say that for each of the 1,000 people in the table below, the mortality risk in the next 10 years is 47 per 1,000.



#Q26. How many people from the table above will survive the next 10 years?

The purpose of this question is to check whether the previously presented explanations were understood by the survey participants. Responses to this question will be analyzed collectively to check the validity of the survey instrument (questionnaire).

- 1 ___ people
- 2 Don't know / hard to say

#Q27. What is the mortality risk for each of the 1,000 people in this table?

The purpose of this question is to check whether the previously presented explanations were understood by the survey participants. Responses to this question will be analyzed collectively to check the validity of the survey instrument (questionnaire).

- 1 ___ per 1,000
- 2 Don't know / hard to say

New screen

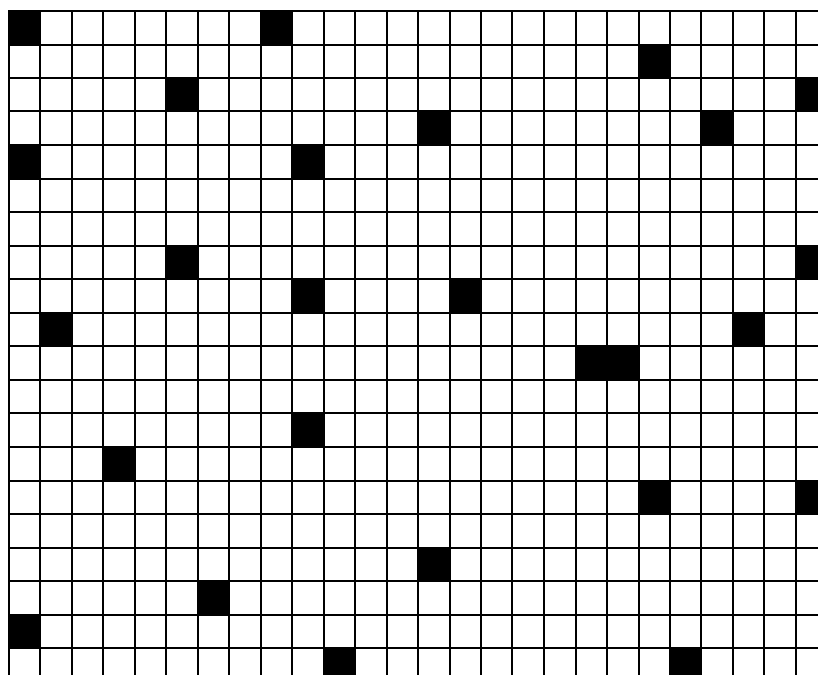
Treatment 4: Correct answer (comprehension)

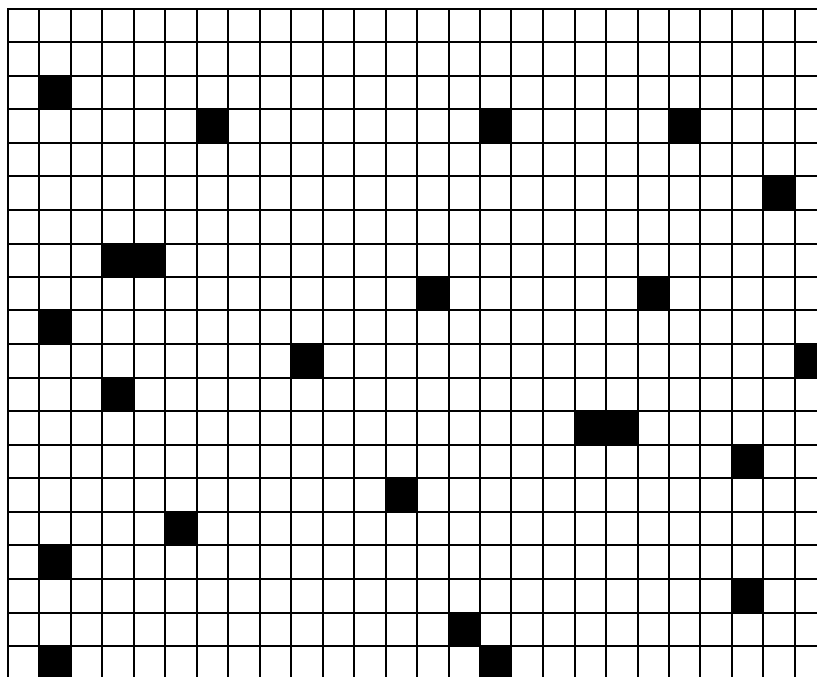
Case A: Displaying the screen below

Case B: Skipping the screen below

The presented table shows 47 people out of 1,000 who will die in the next 10 years. This means that for every 1,000 people in the next 10 years, 953 people will survive.

In other words, we can say that for each of the 1,000 people in the presented table, the risk of dying in the next 10 years is equal to 47 per 1,000.

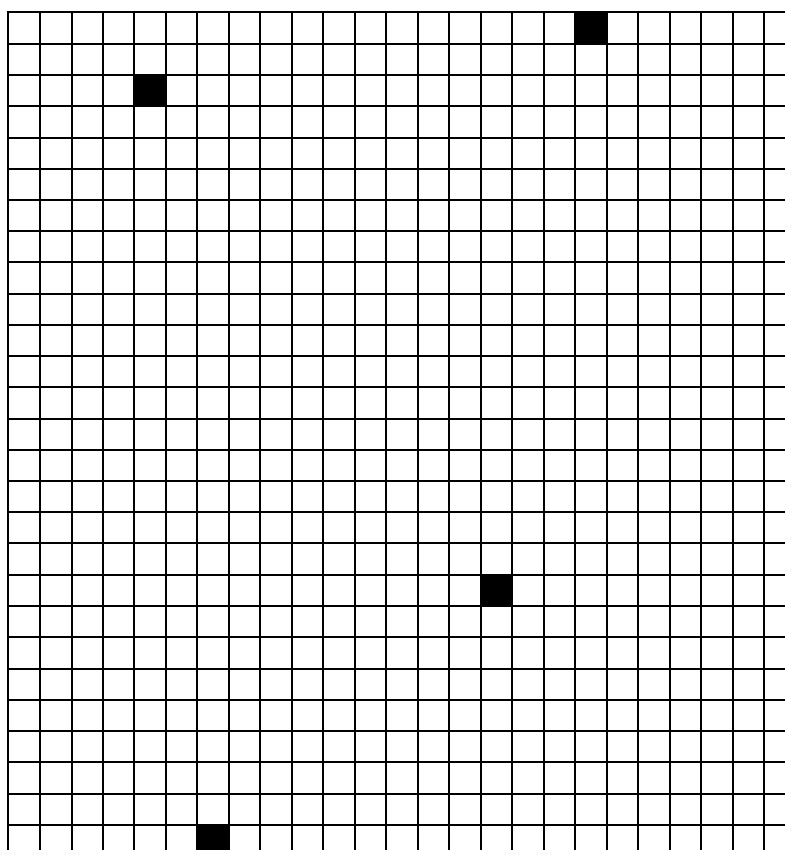


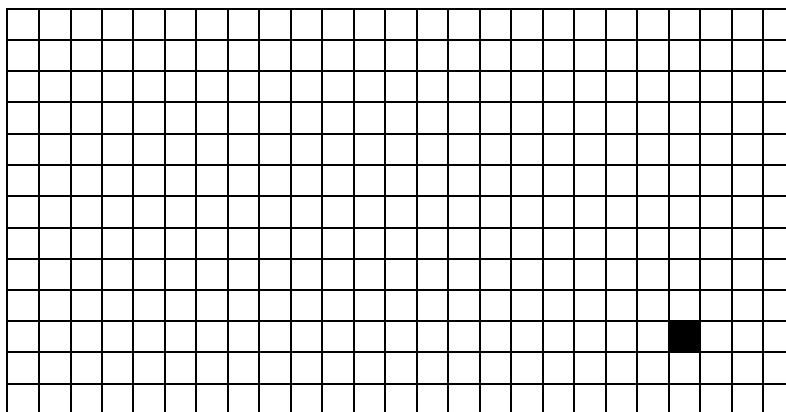


New screen

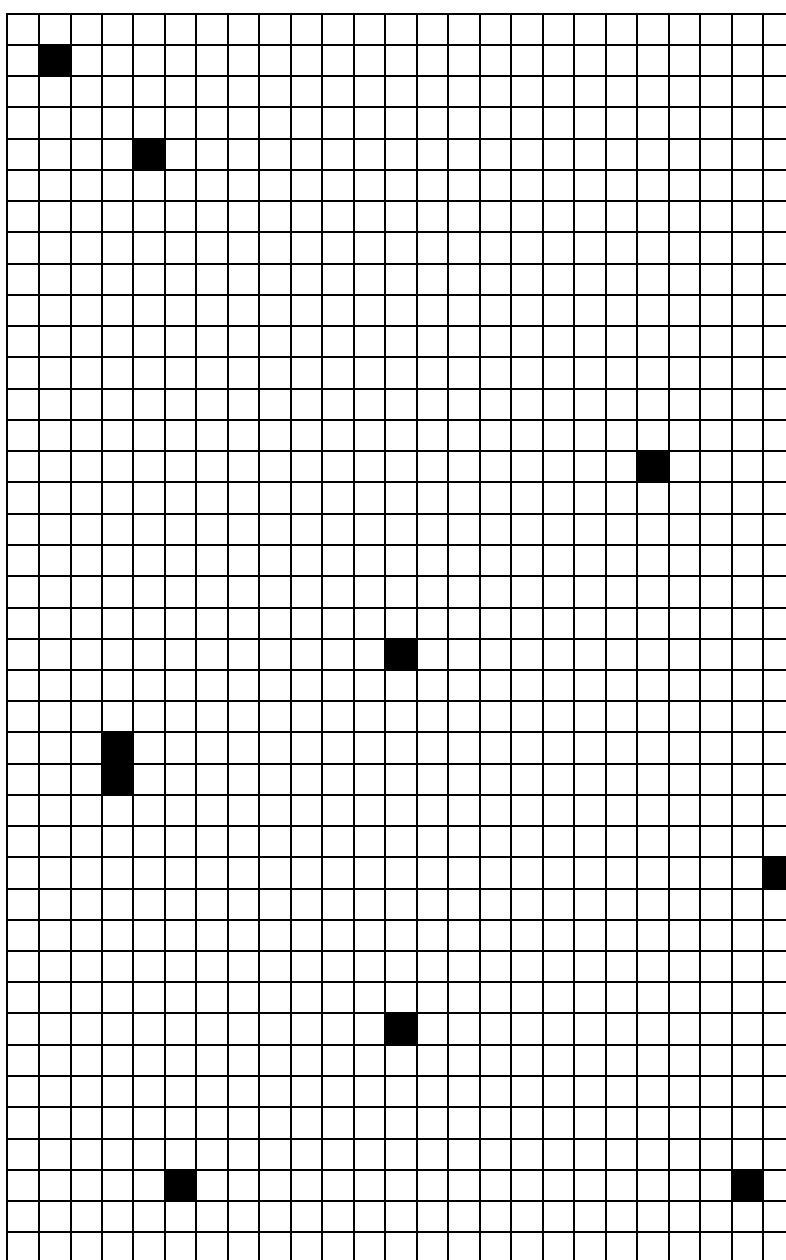
Suppose we have two people whose chances of surviving the next 10 years are as shown in the tables below.

Person 1: Mortality risk = 5 per 1,000 people in the next 10 years.





Person 2: Mortality risk = 10 per 1,000 people in the next 10 years.



#Q28. Which of these people is more likely to survive the next 10 years?

The purpose of this question is to check whether the previously presented explanations were understood by the survey participants. Responses to this question will be analyzed collectively to check the validity of the survey instrument (questionnaire).

- 1 Person 1
- 2 Person 2
- 3 The chances of survival of these two people are the same
- 4 Don't know / hard to say

New screen

Treatment 4: Correct answer (comprehension)

Case A: Displaying the screen below

Case B: Skipping the screen below

Assuming comparing two people whose chances of surviving the next 10 years are as follows:

Person 1: risk of death = 5 in 1,000 over the next 10 years.

Person 2: risk of death = 10 per 1,000 in the next 10 years.

It can be concluded that the first person has a better chance of surviving the next 10 years, since his/hers risk of death is lower.

New screen

The risk of death affects the statistical life expectancy. This value describes the average further life expectancy of a person of a certain age (in other words, the average number of years a person has to live). For example, at birth, it is estimated that the statistical life expectancy in Poland is 73 years for men and 81 years for women. In your case (taking into account your gender and age), the statistical life expectancy is years [number X2 from Table A based on gender and age].

It is worth noting that the information presented is only a (statistical) approximation - because no one can predict the date of someone's death or the reason for it. If you believe that you lead a healthy lifestyle, there is a good chance that the risk of death in your case is lower (and statistical life expectancy - longer). On the other hand, if you believe you are in a high-risk group (e.g., given your family medical history or lifestyle), then the risk is likely to be higher (and statistical life expectancy is shorter). It is worth remembering, however, that the risk of death from cardiovascular disease is never zero, and some diseases (such as heart attack or stroke) come suddenly and unexpectedly.

New screen

In Poland, the average mortality risk from cardiovascular diseases (not taking into account the influence of age and gender) is 47 per 1,000 people over the next 10 years.

#Q29. Taking into account your age, health, lifestyle, and family predisposition, please specify how you rate your mortality risk.

- 1 As significantly smaller than the average for my age group
- 2 As smaller than the average for my age group
- 3 As similar to the average for my age group
- 4 As greater than the average for my age group
- 5 As significantly larger than the average for my age group
- 6 Don't know / Hard to say

#Q30. How do you assess your risk of death from cardiovascular diseases per 1,000 people over the next 10 years?

I estimate my risk of dying from cardiovascular diseases at:

___ per 1,000 people over the next 10 years <control, 0-1000, integers>

F: DCE on risk mortality reduction and life expectancy extension**New screen**

You are about to be asked about your willingness to pay for a reduction in mortality risk. To better understand the problem under study, you can imagine that through the development of medicine, it would be possible to cancel out some of the deaths caused by cardiovascular disease, which would also increase the value of statistical life expectancy.

Please keep in mind your financial capacity and the fact that there are many other needs (daily expenses, entertainment, or medical expenses related to other diseases). Please do not consider possible financial uncertainties in future years.

New screen

Suppose a new drug, well researched (with no side effects) and approved by the Ministry of Health and international organizations (including the European Medicines Agency), reduces the mortality risk associated with cardiovascular diseases by strengthening the body's immunity. Taking this drug reduces the mortality risk by the stated number (per 1,000 people over the next 10 years). This means that for every 1,000 people taking this drug over the next 10 years, a certain number fewer people will die. This would also increase statistical life

expectancy. In addition, taking the drug would improve quality of life and eliminate the need for hospitalization for cardiovascular causes.

The drug would be available to the general public, however, it would not be free - a certain fee would have to be paid to use it. To be effective, the drug would have to be taken once a year for a period of 10 years. The drug could be taken in different forms (e.g. tablets or injections), and each form of intake would be equally effective.

Note: Your responses matter! The results of this survey will be presented to local, national, and European authorities and may influence future regulations and health policies (among other things, they may serve to assist in decision-making vis-à-vis various health interventions or resource allocation).

New screen

In a moment, we will show you 12 situations describing possible scenarios regarding the launch of a new cardiovascular disease drug that would reduce the mortality risk and hospitalization due to cardiovascular diseases. Each situation will consist of three options to choose from. One will be to forgo taking the new drug and have no associated costs, and the other two will be to reduce the mortality risk and the annual cost offered by the newly introduced drug.

In answering the following questions, please assume that the new drug's effectiveness and safety are exactly as described.

IN ADDITION, WHEN MAKING CHOICES, PLEASE REMEMBER THAT:

- Every household needs money for various other expenses.
- There are many purposes for which more money can be spent (including recreation or savings). Spending money on medicines or other health-related expenses means that your remaining budget for other purposes (e.g., recreation or savings) will be smaller.
- If you think a particular option is too expensive for what it offers - and you would not choose to pay that much for it - please do not choose it.
- One option is always to opt out of taking the new drug - an option that means no change and does not incur any additional fees for you. If you feel that all others are too expensive, please choose this option.

Treatment 1 Disclosure of attributes (DCE risk mortality)

Case A: Presenting the respondent with the levels of attributes they will see in the survey

Case B: Skipping the screen

The table below shows a list of attributes with descriptions that were used in the study.

Attribute	Attribute levels
Mortality risk reduction	1 fewer deaths per 1,000 people over the next 10 years 2 fewer deaths per 1,000 people over the next 10 years 4 fewer deaths per 1,000 people over the next 10 years
Annual cost	Treatment 2 Cost vector (DCE risk mortality) Case A: Low-cost vector: 50, 100, 150, 200, 250, 300 PLN Case B: Medium-cost vector: 100, 200, 300, 400, 500, 600 PLN Case C: High-cost vector: 200, 400, 600, 800, 1 000, 1 200 PLN

New screen

Which of the options presented below do you think is best for you?

Please treat each situation independently of the others.

1 of 12 choice cards (#Q31, #Q32, #Q33, #Q34, #Q35, #Q36, #Q37, #Q38, #Q39, #Q40, #Q41, #Q42)

	Drug A	Drug B	Resignation from taking the drug
Mortality risk reduction	2 fewer deaths per 1,000 people over the next 10 years	4 fewer deaths per 1,000 people over the next 10 years	Risk of dying from disease X will remain the same
Annual cost	100 PLN	300 PLN	0 PLN
Your choice:	☐	☐	☐

Reminder:

In Poland, the average mortality risk from cardiovascular diseases (not taking into account the influence of age and gender) is 47 per 1,000 people over the next 10 years. In the previous question, you estimated your risk of dying from circulatory system diseases at per 1,000 people over the next 10 years.

G: Debriefing, consequentiality, and opt-out reasons**New screen**

#Q43. To what extent do you agree or disagree with the following statements?

	I strongly disagree	I disagree	I disagree to some extent	Neither disagree nor agree / Difficult to say	I agree to some extent	I agree	I strongly agree
#Q43_1. I had enough information to make a decision.							
#Q43_2. I had problems understanding the selection situation							
#Q43_3. I was confident in the decisions I made.							
#Q43_4. The descriptions were too long.							
#Q43_5. The descriptions were not objective - they were in favor of certain solutions.							
#Q43_6. Please select 'I agree'. Attention check							
#Q43_7. I think that my answers may contribute to the decisions made by the authorities.							

New screen

If the respondent chose the status quo at least once

#Q44. In at least one of the questions, you indicated that you would not be willing to choose a drug that reduces the mortality risk. We would like to know what was the reason for this. Please mark all the reasons that influenced such a decision:

- 1 I don't have enough money, although I would want the drug to be introduced.
- 2 The drug was too expensive concerning the benefits gained.
- 3 I do not believe in the effectiveness of this drug.
- 4 Benefits of introducing the drug were too small.
- 5 Someone else (e.g., the state) should pay for the introduction of such a drug.
- 7 I see no need for such a drug.
- 8 I already pay enough taxes, and it should cover such health care expenses.
- 9 Other reasons. Please, specify: ____.

H: Additional contingent valuation questions (DBDC & OE)**Treatment 3: Double Bounded Dichotomous Choice - X**Case A: $X = 200$ PLNCase B: $X = 400$ PLNCase C: $X = 600$ PLN

New screen

#Q45. Would you be willing to pay $[X]$ per year (for a period of 10 years) for the mentioned drug, which reduced the mortality risk and hospitalization due to cardiovascular disease by 1 in 1000?

Please keep in mind your financial capacity and the fact that there are many other needs (daily expenses, entertainment, or medical expenses related to other diseases). Please provide a specific amount without considering possible financial uncertainties in future years.

1 Yes

2 No

If Q45=Yes

New screen

#Q46A. Would you be willing to pay $[X*2]$ per year (for a period of 10 years) for the mentioned drug, which reduced the mortality risk and hospitalization due to cardiovascular disease by 1 in 1000?

Please keep in mind your financial capacity and the fact that there are many other needs (daily expenses, entertainment, or medical expenses related to other diseases). Please do not consider possible financial uncertainties in future years.

1 Yes

2 No

If Q45=No

New screen

#Q46B. Would you be willing to pay $[X/2]$ per year (for a period of 10 years) for the mentioned drug, which reduced the mortality risk and hospitalization due to cardiovascular disease by 1 in 1000?

Please keep in mind your financial capacity and the fact that there are many other needs (daily expenses, entertainment, or medical expenses related to other diseases). Please do not consider possible financial uncertainties in future years.

1 Yes

2 No

#Q47. What is the maximum amount of money per year you would be willing to pay (over a period of 10 years) for the mentioned drug, which reduced the mortality risk and hospitalization due to cardiovascular disease by **1 in 1000**?

Please keep in mind your financial capacity and the fact that there are many other needs (daily expenses, entertainment, or medical expenses related to other diseases). Please do not consider possible financial uncertainties in future years.

___ PLN <range check based on Q45 and A46A/Q46B answers>

New screen

Thank you for your time and participation in the survey!



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