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Preference-Based Assessments

Preference Variation: Where Does Health Risk Attitude Come Into the Equation?

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ABSTRACT

Objectives: Decisions about health often involve risk, and different decision makers interpret and value risk information differently. Furthermore, an individual's attitude toward health-specific risks can contribute to variation in health preferences and behavior. This study aimed to determine whether and how health-risk attitude and heterogeneity of health preferences are related.

Methods: To study the association between health-risk attitude and preference heterogeneity, we selected 3 discrete choice experiment case studies in the health domain that included risk attributes and accounted for preference heterogeneity. Health-risk attitude was measured using the 13-item Health-Risk Attitude Scale (HRAS-13). We analyzed 2 types of heterogeneity via panel latent class analyses, namely, how health-risk attitude relates to (1) stochastic class allocation and (2) systematic preference heterogeneity.

Results: Our study did not find evidence that health-risk attitude as measured by the HRAS-13 distinguishes people between classes. Nevertheless, we did find evidence that the HRAS-13 can distinguish people's preferences for risk attributes within classes. This phenomenon was more pronounced in the patient samples than in the general population sample. Moreover, we found that numeracy and health literacy did distinguish people between classes.

Conclusions: Modeling health-risk attitude as an individual characteristic underlying preference heterogeneity has the potential to improve model fit and model interpretations. Nevertheless, the results of this study highlight the need for further research into the association between health-risk attitude and preference heterogeneity beyond class membership, a different measure of health-risk attitude, and the communication of risks.

Keywords: choice modeling, discrete choice experiment, latent class, preference elicitation, preference heterogeneity, risk attitude.

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Introduction

Decisions about health often involve risk, but at the same time it must be recognized that different decision makers interpret and value risk information differently.[1,2] For example, some people prefer a small chance of full recovery, over a more certain but moderately good outcome, and others vice versa. Examples such as these portray why patients' decisions sometimes conflict with physicians expectations or advice.[3] The psychological construct that describes how people make decisions under uncertainty is called risk attitude,[4] which has been shown to affect health policy decisions on an aggregate level when incorporated in analyses.[5,6] Also on an individual level, attitude toward health-specific risks contributes to heterogeneity in health preferences and behavior.[7,8] Insights into the relationship between risk attitude and preference heterogeneity in health can improve the accuracy with which uptake and adherence to treatment are predicted.[9,10] In addition, they can be informative when alternatives largely vary in terms of benefit-risk or when treatment outcomes are highly uncertain,[11,12] for example, by providing information tailored to varying health risk attitudes in clinical practice or for patient subgroup considerations in benefit-risk assessments. Although researchers generally agree that risk attitude plays a role in healthcare decision making, there is no consensus on how to operationalize it.[13] Risk attitude is often domain specific[14,15]; it covers both risk perception and risk-taking behavior, although these can be conflicting concepts,[15,16] and risk attitudes as measured in surveys do not always translate to the real world.[17,18] As such, studying the relationship between health-risk attitude and health preferences is rather complex.

Health preferences are often elicited via discrete choice experiments (DCEs), a method to quantify preferences for alternative health interventions by letting respondents repeatedly trade-off alternatives that are described using a variety of attributes and levels.[19] They are increasingly used to incorporate patients' preferences in various medical contexts that concern benefit-risk decision making, such as clinical guidelines, regulatory decision making, and health technology assessment of these health interventions.[19-21] Many of the health interventions described in DCEs include one or more risk attributes. Harrison et al[22] systematically reviewed DCEs with a risk attribute in the field of health and found that few of these DCEs incorporated individual characteristics underlying risk preferences. Only Tsuge et al[23] elicited subjective risk perception and found that it influenced willingness to pay in their DCE. None of the other identified studies elicited risk attitude; instead they derived it from responses to the choice tasks and used this information in their statistical analysis. In line with the increasing use of and demand for analyzing heterogeneity in DCEs,[19,24,25] Russo et al[13] systematically reviewed individual characteristics underlying the decision-making process and their relation to preference heterogeneity. They identified risk attitude as 1 important, yet marginally studied, factor relating to preference heterogeneity; experts agreed with this assessment.[12] Furthermore, studies that assess risk in health-related DCEs focus on risk communication rather than risk attitude.[26,27] Although individual characteristics such as health numeracy, health literacy, and decision-making style (also identified by Russo et al[12]) are increasingly found to be related to preference heterogeneity,[28,29] the complexities associated with the operationalization of risk attitude hamper studying the relationship between risk attitude and preference heterogeneity.[13]

Therefore, the purpose of this study is to determine whether and how health-risk attitude and heterogeneity of health preferences are related by means of 3 case studies, using the relatively new 13-item Health-Risk Attitude Scale (HRAS-13), which aims to overcome some of the operational complexities.[16] To assess the relationship between the HRAS-13 and heterogeneity, we studied 2 types of heterogeneity, namely, (1) stochastic class assignment and (2) systematic preference heterogeneity.

Methods

Case Studies

To study the association between health-risk attitude and heterogeneity of preferences, we selected 3 DCE case studies in the health domain that had at least 1 attribute that implicitly or explicitly concerned risks and for which we could gain the authors' consent to share the data for this purpose. The studies differed in terms of their topic, country, study population, number of respondents, and their DCE design leading to an increased generalizability of the results. An overview of the case studies and their DCE designs can be found in Table 1.[30-32] Attributes and levels were selected based on literature reviews, focus groups, and interviews; these are presented in Table 2. The first case study concerned the treatment preferences of patients with multiple sclerosis (MS) in The Netherlands, France, and the UK.[30] Inclusion criteria were the following: aged 18 years or older, diagnosis of MS, and living in one of these 3 European countries. Respondents were recruited online via the commercial survey sampling company Survey Engine (N = 753). Three of 4 attributes were explicitly described as risks to survey respondents. The second study analyzed preferences regarding antibiotics usage in Sweden.[31] An online sample of respondents between 18 and 65 years old was recruited from the Swedish general public (N = 378). Respondents were recruited online via Dynata, a commercial survey sample provider. Three of 5 attributes concerned risk, 2 of them in percent and the third in words. The third study concerned care for hip and knee osteoarthritis (HKOA) in The Netherlands.[32] Respondents aged 45 years and older with knee or hip osteoarthritis were recruited online, also via Dynata (N = 648). In contrast to the other 2 studies, none of the attributes were explicitly described to respondents as being related to risks. Nevertheless, based on the relationship between time preference and risk aversion, "waiting time in weeks" was classified as a risk attribute.[33,34] The number and type of professionals involved were also classified as a risk attribute because health

Table 1. Case study and DCE design characteristics.

Characteristics	Study 1 Visser et al[30]	Study 2 Ancillotti et al[31]	Study 3 Arslan et al[32]
Case studies			
Topic	Multiple sclerosis	Antibiotics	HKOA
Country	The Netherlands, France, United Kingdom	Sweden	The Netherlands
Study population	Patients with MS, ≥18 years old	General public, 18-65 years old	HKOA patients, ≥45 years old
Number of respondents	753	378	648
DCE design			
Number of attributes	4	5	6
Number of choice sets per block	15	16	12
Number of blocks	2	3	2
Number of alternatives	3 including opt-out	2	2
Risk attributes	Risk of relapse (%), reducing disease progression (%), risk of side effects (words and %)	Contribution to resistance (words), risk of side effects (%), treatment failure (%)	Waiting time in weeks (words), professionals involved (words)
Number of latent classes in original study	2	3	4

Note. Attributes and levels were selected based on literature review, focus groups, and interviews; they are presented in Table 2.
DCE indicates discrete choice experiment; HKOA, hip and knee osteoarthritis; MS, multiple sclerosis.

Table 2. Attributes and levels.

	Study 1—MS Attributes	Levels	Study 2—antibiotics Attributes	Levels	Study 3—HKOA Attributes	Levels
1.	Risk of relapse*	30% less risk	Contribution to resistance*	Low	Waiting time in weeks*	0
		50% less risk		Medium		2
		70% less risk		High		4
2.	Reducing disease progression*	20% less progression	Number of days treatment	3 days	Professionals involved*	GP
		40% less progression		7 days		Orthopedist
		60% less progression		14 days		GP and orthopedist
3.	Risk of side effects*	Very common mild (> 10%)	Risk of side effects*	1%	Price in Euros	0
		Common moderate (1%-10%)		5%		45
		Rare severe (0.1%-1%)		10%		90
				20%		
4.	Mode of administration	Injections (1× per week)	Treatment failure*	80%	Time per consult in minutes	10
		Injections (3× per week)		85%		15
		Pills (1× per day)		90%		30
		Pills (2× per day)		95%		
		Implant (1× per year)				
		Implant (1× per 3 years)				
5.			Costs	100 kr.	Travel time in kilometers	1
				250 kr.		7
				400 kr.		20
				1000 kr.		
6.					Equipment available	Direct
						Indirect

GP indicates general practitioner; HKOA, hip and knee osteoarthritis; kr., Swedish Krona; MS, multiple sclerosis.
*Attributes with an asterisk implicitly or explicitly concerned risks.

anxiety increases the belief that specialist referral is needed, and health anxiety was found to be driven by risk aversion.[35,36] More details about the 3 studies are published elsewhere.[30-32]

DCE Design and Questionnaire

In all studies, a Bayesian heterogeneous DCE design was created using Ngene ChoiceMetrics software[37] to maximize D-efficiency. Initial priors were based on literature, focus groups, and interviews with experts or members of the study population in the prepiloting phase. Based on the results of a standard multinomial logit model, the priors and the design were optimized once 10% of the required sample completed the questionnaire. In study 1, the final experimental design contained 30 choice tasks that were divided into 2 blocks of 15 choice tasks. Each choice task had 2 generic alternatives ("treatment 1" and "treatment 2") that were characterized by a selection of attribute levels, and the third alternative ("no treatment") allowed respondents to not choose any of the alternatives presented (opt-out). The design of the second study consisted of 48 unique choice tasks divided over 3 blocks of 16 choice tasks. Each choice task had 2 generic alternatives. In study 3, the design consisted of 24 choice tasks and was divided into 2 blocks of 12 choice tasks. Again, each choice task had 2 generic alternatives. Examples of the choice tasks are given in Appendix Figures 1 to 3 in Appendix A in Supplemental Materials found at https://doi.org/10.1016/j.jval.2022.05.005.

Table 3. Respondent characteristics per study.

Characteristic	Category	Study 1—MS n (%)	Study 2—antibiotics n (%)	Study 3—HKOA n (%)
n		753 (100)	378 (100)	648 (100)
HRAS-13 score, mean (SD)		44.5 (9.2)	60.2 (9.8)	49.0 (5.4)
HRAS-13 score, median		46	60	50
HRAS-13 score, range		18-70	19-86	29-65
Health, mean (SD)		60.6 (20.3)	-	68.8 (19.6)
Health, median		65	Good	73
Health, categories	Very poor	-	6 (1.6)	-
	Poor	-	38 (10.1)	-
	Neutral	-	113 (29.9)	-
	Good	-	163 (43.1)	-
	Very good	-	58 (15.3)	-
Health, categories median split	High: > median	386 (51.3)	58 (15.3)	323 (49.8)
	Low: ≤ median	367 (48.7)	320 (84.7)	325 (50.2)
Age, mean (SD)		42.0 (12.1)	43.3 (13.6)	61.7 (8.9)
Sex	Female	512 (67.9)	208 (55.0)	359 (55.4)
	Male	241 (32.1)	169 (44.7)	289 (44.6)
	Other	0 (0.0)	1 (0.3)	0 (0.0)
Education level	Low	188 (25.0)	70 (18.5)	207 (31.9)
	Medium	201 (26.7)	108 (28.6)	275 (42.4)
	High	356 (47.3)	194 (51.3)	164 (25.3)
	Other	8 (1.1)	6 (1.6)	2 (0.3)
Health literacy	Inadequate	96 (12.7)	8 (2.1)	-
	Problematic	497 (66.0)	117 (31.0)	-
	Sufficient	160 (21.2)	253 (66.9)	-
Numeracy	Inadequate	51 (6.8)	23 (6.1)	-
	Problematic	331 (44.0)	154 (40.7)	-
	Sufficient	371 (49.3)	201 (53.2)	-

HKOA indicates hip and knee osteoarthritis; HRAS-13, 13-item Health-Risk Attitude Scale; MS, multiple sclerosis.

To assess health-risk attitude, we used the 13-item HRAS-13.[16] The HRAS-13 is context specific, and its items relate to medical treatment, the importance of health, general attitude toward risk taking in health and care, and consideration of the future consequences of health behaviors. Advantages of using this scale are that (1) context-specific scales are found to better predict risk behavior[17,38]; (2) it overcomes the discussion about whether risk attitude is context dependent or whether a general risk attitude exists[15,16]; and (3) it avoids the need to differentiate between risk-taking behavior and risk perception.[15,16] The items of the HRAS-13 were rated on a 7-point Likert scale from "completely disagree" to "completely agree." Total scores for the HRAS-13 were obtained by reverse-scoring 7 of the items that are phrased negatively and then summing the scores to each item. Scores range between 13 and 91. Respondents with a lower HRAS-13 score are more health risk averse, whereas a higher HRAS-13 score indicates a more risk-prone attitude toward health risks. In addition, the questionnaires contained questions about health, age, sex, and education level. Health was measured using a visual analog scale ranging from 0 to 100 in study 1 and study 3, while using a 5-point Likert scale from "very poor" to "very good" in study 2. Age was measured on a continuous scale, with sex as "female," "male," or "other." Education level was measured according to the European Qualification Framework[39] and categorized as "low," "medium," or "high" in accordance with the Dutch Qualification Framework and Statistics Netherlands.[40,41] In addition, study 1 and study 2 also contained questions about health literacy and numeracy. Health literacy was measured using the Communicative Health Literacy and Critical Health Literacy scales.[42] The scale consists of 5 items on a 4-point Likert scale that ranges from "never" to "always." Based on the average scoring system in de Bekker-Grob et al[43,44] and the 3 categories by Ancillotti et al,[31] respondents with an average score of 2 or lower were categorized as "inadequate," those between 2 and 3 were categorized as "problematic," and those with an average score larger than 3 were deemed "sufficient." The Dutch version of the scale[45] has more items than the original (Japanese) version[42] and the Swedish version.[46] In addition, the Dutch version uses a 4-point Likert scale rather than a 5-point Likert scale. Study 1 was based on the Dutch version (and translated from Dutch to English and French); study 2 was based on the Swedish version. For comparability between studies, health literacy was calculated using only the 5 items that were in the Swedish version, and responses in study 2 were recoded so that they were also rated on a 4-point Likert scale (divide each item

Table 4. Overview results per study.

Type of heterogeneity	Class	Study 1—MS	Coeff.	*P* value	Study 2—antibiotics	Coeff.	*P* value	Study 3—HKOA	Coeff.	*P* value
Stochastic class allocation	1	HRAS	−0.002	.839	HRAS	0.018	.316	HRAS	0.007	.794
	2	HRAS	0.000	-	HRAS	−0.002	.924	HRAS	−0.001	.980
	3	-	-	-	HRAS	0.000	-	HRAS	0.036	.301
	4	-	-	-	-	-	-	HRAS	0.000	-
Systematic heterogeneity	1	Risk relapse (%)	−0.009	<.001	Resistance (med)	0.012	.262	Waiting time	−0.023	.001
		Progression (%)	−0.017	<.001	Resistance (high)	0.004	.794	Orthopedist	0.026	.327
		Side effects (mod.)	−0.002	.391	Side effects (5%)	0.001	.949	GP and orthopedist	−0.002	.953
		Side effects (sev.)	−0.002	.002	Side effects (10%)	0.000	.989			
					Side effects (20%)	−0.001	.934			
					Treatment failure (%)	−0.004	.577			
	2	Risk relapse (%)	0.012	.003	Resistance (med)	−0.010	.320	Waiting time	−0.004	.441
		Progression (%)	−0.007	.026	Resistance (high)	−0.005	.578	Orthopedist	0.031	.167
		Side effects (mod.)	0.002	.772	Side effects (5%)	0.002	.834	GP and orthopedist	0.026	.198
		Side effects (sev.)	0.003	.318	Side effects (10%)	0.012	.285			
					Side effects (20%)	0.014	.197			
					Treatment fail (%)	−0.016	.019			
	3	-	-	-	Resistance (med)	0.007	.466	Waiting time	0.036	.001
					Resistance (high)	−0.004	.733	Orthopedist	−0.041	.317
					Side effects (5%)	−0.001	.949	GP and orthopedist	0.023	.616
					Side effects (10%)	−0.005	.655			
					Side effects (20%)	−0.023	.057			
					Treatment fail (%)	−0.001	.847			
	4	-	-	-	-	-		Waiting time	0.008	.053
								Orthopedist	0.025	.913
								GP and orthopedist	0.027	.056

Coeff. indicates coefficient; GP, general practitioner; HKOA, hip and knee osteoarthritis; HRAS, Health-Risk Attitude Scale; med, medium; mod., moderate; MS, multiple sclerosis; sev., severe.

score by 5 and multiply by 4/5). Numeracy was measured using the 3-item version of the subjective numeracy scale.[47] Based again on de Bekker-Grob et al[43,44] and Ancillotti et al,[31] items were scored on a 6-point Likert scale ranging from “not good at all/never” to “extremely good/very often.” Respondents with an average score below 2 were categorized as “inadequate,” those with a score between 3 and 4 were categorized as “problematic,” and those with an average score higher than 5 were deemed “sufficient.”

Analysis of Health-Risk Attitude and Preference Heterogeneity

Panel latent class models were used to analyze heterogeneity of preferences. These models account for the multiple choice sets each respondent completed (ie, panel structure), and they capture unobserved heterogeneity of preferences using a discrete number of classes (ie, latent classes).[48-50] Following random utility theory, class allocation of respondent n in class c is based on choices for choice set s of each alternative j and is given by $U_{nsj|c}$. The utility consists of an observable component V and a random component $\varepsilon_{nsj|c}$ that is formally written as follows:

$$U_{nsj|c} = V(X_{nsj},\ \beta_c) + \varepsilon_{nsj|c}. \tag{1}$$

Here β_c is a class-specific vector describing the preference weights of the attributes and levels X'_{nsj} for respondent n for choice set s in alternative j. The exact model specification differed per study; the specification of the alternative specific constant(s), linearity of the attributes, and the number of classes were based on model fit and with consideration for class size and interpretability of the main-effects model.

To understand whether and how health-risk attitude and preference heterogeneity are related, we analyzed 2 types of heterogeneity, namely, (1) stochastic class assignment and (2) systematic preference heterogeneity. Both types of heterogeneity were included jointly to disentangle the different potential sources of preference heterogeneity. The impact of health-risk attitude on stochastic class assignment was included to analyze whether health-risk attitude could distinguish preferences between classes, that is, whether it distinguished preferences for risk-related attributes and nonrisk-related attributes. For matters of completeness, the class assignment model also included other variables based on their relationship with health-risk attitude or preference heterogeneity. The propensity of class membership ϕ_{nc} is specified as a linear-in-parameters function consisting of a constant term $\delta_{0|c}$ plus the variables health[7,16,28] (dichotomized based on median split, good vs rest), age[28,51] (continuous), sex[4,16,28,51] (male vs female), education level[4,28] (high vs rest), and if applicable numeracy[28,51] and health literacy[28,29] (sufficient vs rest); thus:

$$\begin{aligned}\phi_{nc} = {} & \delta_{0|c} + \gamma_{1|c}\text{HRAS score}_n + \gamma_{2|c}\text{good health}_n + \gamma_{3|c}\text{age}_n \\ & + \gamma_{4|c}\text{male}_n + \gamma_{5|c}\text{high education}_n + \gamma_{6|c}\text{sufficient literacy}_n \\ & + \gamma_{7|c}\text{sufficient numeracy}_n + \omega_{nc}.\end{aligned} \tag{2}$$

The stochastic term w_{nc} is assumed to be extreme value type 1 (Gumbel) independent and identically distributed across classes, yielding a polytomous multinomial logit model for the probability of class membership:

$$\pi_{nc} = \frac{\exp(\overline{\phi_{nc}})}{\sum_{c'=1}^{C}\exp(\overline{\phi_{nc'}})}. \tag{3}$$

Note that the coefficient vector for 1 class must be set to 0.

Statistically significant γ coefficients (as indicated by $P < .05$) indicate that a certain variable contributed to the class assignment model. For example, a positive and statistically significant γ coefficient of HRAS score in class 1 would mean that respondents with higher HRAS scores are more likely to be allocated to class 1 than the reference class. Nevertheless, a nonsignificant coefficient means that differences in HRAS scores do not explain differences in overall preference structures between the classes.

In parallel, we assessed the relationship between health-risk attitude and systematic preference heterogeneity by interacting the risk-related attributes with respondents' health-risk attitude. A statistically significant HRAS interaction term (again as indicated by $P < .05$) with a risk-related attribute, for example, in class 1, is interpreted as health-risk attitude explaining preference heterogeneity of that attribute within that class.

To assess the impact of including health-risk attitude, in each study, we compared log-likelihood of the model that included health-risk attitude in the class allocation model and used interactions with a model that did not do either but was equal in all other aspects. Log-likelihood statistics were compared using likelihood ratio tests, given that the number of classes is equal between models. All analyses were performed in Nlogit 6.

Results

Respondents

Given the varying study contexts, inclusion criteria, and study designs, the 3 studies had different types of respondents (see Table 1[30-32] for an overview of the case studies). The studies consisted of 753, 378, and 648 respondents, respectively. In study 2, the general public sample, HRAS-13 scores were generally higher (more positive attitude toward health risks) and more dispersed than in the MS sample (study 1) and the HKOA sample (study 3). In study 1, respondents were less healthy (mean = 60.6) than in study 3 (mean = 68.8); they were younger (mean = 42.0), mostly female (67.9%), and highly educated (47.3%). Furthermore, the sample of study 1 was less literate and slightly less numerate than in study 2. In the second study, most people had a good (43.1%) or very good (15.3%) health. The sample of study 2 was slightly older than in the first study, but younger than in the third. As in study 1, most respondents were highly educated (51.3%). In study 3, respondents were oldest (mean = 61.7), 55.4% were female, and fewer (25.3%) were highly educated than in the other studies. No data were collected on health literacy and numeracy. An overview of these respondent characteristics can be found in Table 3, whereas more information about the relationship between HRAS-13 scores and other background variables is presented in Appendix Table 1 in Appendix B in Supplemental Materials found at https://doi.org/10.1016/j.jval.2022.05.005.

Health-Risk Attitude and Preference Heterogeneity

An overview of the results per study is presented in Tables 4 and 5 described below; for further information, the full results are presented in Appendix Tables 2 to 4 in Appendix C in Supplemental Materials found at https://doi.org/10.1016/j.jval.2022.05.005. In none of the studies were HRAS-13 scores statistically significantly related to stochastic classification of preferences. This indicates that parameters in the utility function were not jointly dependent on health-risk attitude for any of the classes in any of the studies. Nevertheless, numeracy was related to class allocation (P = .02) in study 1. In study 2, age (P = .004) and health literacy contributed to class allocation (P = .012) in class 1 and 2, respectively. In study 3, age explained class allocation in 2 classes (P = .004 and P = .040).

In contrast, systematic heterogeneity as measured by interactions between health-risk attitude and risk attributes was present in some risk attributes of the studies. In study 1, the MS patient sample with 3 risk attributes phrased using percent, we found systematic preference heterogeneity for all risk attributes in the first and largest class. In this class, health-risk attitude significantly moderated the effect of reducing the risk of relapse and reducing disease progression ($P < .001$ for both) and the risk of rare severe side effects (P = .020). In the second class, only the interaction between health-risk attitude and reducing risk of relapse (P = .003) was significant. In addition, the second study, concerning the antibiotics context with a general public sample, had 3 classes and 3 risk attributes. Health-risk attitude explained part of the heterogeneity for treatment failure rate (P = .019) in one of the classes but not in the other 2. Nevertheless, the interaction effects with the other risk attributes were not significant in any of the classes. In the third study about patients' preferences for HKOA treatment, 2 attributes implicitly concerned risk. In 2 of the 4 classes, health-risk attitude explained heterogeneity of preferences for waiting time (P = .001 for both) but not for professionals involved.

As shown in Table 5, inclusion of HRAS-13 scores significantly improved the model fit only in study 3 (χ^2 = 37.9, df = 15, $P < .001$). In the other studies, the improvement was not statistically significant.

Discussion and Conclusions

Hence, where does health-risk attitude come into the equation when researching preference variation? Our study did not find

Table 5. Model fit per study.

Statistic		Study 1 - MS	Study 2 - antibiotics	Study 3 - HKOA
Log-likelihood (-)	Excluding HRAS	9389.98	3009.38	4215.38
	Including HRAS	9383.08	2999.73	4196.44
Number of parameters	Excluding HRAS	29	41	47
	Including HRAS	38	61	62
Likelihood ratio test	χ^2	13.8	19.3	37.9
	df	9	20	15
	P value	.130	.502	<.001

HKOA indicates hip and knee osteoarthritis; HRAS, Health-Risk Attitude Scale; MS, multiple sclerosis.

evidence that health-risk attitude as measured by the HRAS-13 distinguishes people between classes. Nevertheless, we did find evidence that the HRAS-13 can distinguish people's preferences for some risk attributes within classes. This association between health-risk attitude and preference heterogeneity was stronger in the case studies where respondents were sampled from a patient population than in the case study that used a general public sample. Respondents in the patient samples were also more health risk averse than members of the general public. In the first case study, which used a patient sample, health-risk attitude explained the heterogeneity of preferences for most attributes in both classes, but it did not significantly improve the model fit. In the third study, which also used a patient sample, health-risk attitude was related to heterogeneity of preferences for one attribute in 2 of 4 health preference classes. Although the 2 risk attributes of this study only implicitly concerned risk, it was the only study in which the model fit statistically significantly improved by incorporating health-risk attitude.

Furthermore, we found that numeracy, health literacy, and age affected stochastic class allocation, meaning that these characteristics could distinguish preferences between classes for risk-related attributes and nonrisk-related attributes. In the study where numeracy affected class allocation, all risk attributes were phrased using percent. In the study where health literacy affected class allocation, one of the risk attributes was described in words. Moreover, numeracy and literacy were among the characteristics that improved external validity when accounted for in preference heterogeneity in de Bekker-Grob et al[28] and among the psychological constructs with the strongest consensus to be included in preference studies in the review of Russo et al.[12] Our results suggest that risks are in some way related to preference heterogeneity, either directly when health-risk attitude distinguishes people's preferences within classes or indirectly when people have varying levels of numeracy and literacy.

The relevance of these results is threefold. First, the impact of health-risk attitude on preferences should be explored beyond class membership by interacting the health-risk attitude with the risk-related attributes. This is expected to be mostly relevant in contexts where alternatives largely vary in terms of benefit-risk, when treatment outcomes are highly uncertain, or when patients are risk averse. In those contexts, accounting for health-risk attitude has the potential to improve model fit and model interpretations. Second, the impact of health-risk attitude on preferences should be explored using a different measure than the HRAS-13. Given that we did not find strong evidence for this using the HRAS-13, which is a health-specific instrument of which the items cover a broad range of health domains,[16] an option would be to use a more targeted measure of health-risk attitude in DCEs. In addition, one could research the relationship between health preference heterogeneity and measures that use a narrower definition of risk attitude (eg, the standard gamble method[52-54] or the Balloon Analog Risk Task[55]). Such studies can confirm whether indeed health-risk attitude is not linked to preferences as strongly as anticipated[12,13] or whether it could be explained by the relatively low levels of variance in the HARS-13 scores in the case studies. As outlined in the Methods section, we do recommend sticking to a health-specific measure of risk attitude. Third, given that numeracy and health literacy were found to affect stochastic class allocation, our results add to existing literature that stresses the importance of the communication of risks (ie, presentation, framing, training materials, and analysis) in DCEs (eg, Harrison et al,[22] Veldwijk et al,[29] and Peters et al[56]). In this study, we analyzed a wide range of risk attributes. Although we did not observe clear differences in the relationship between health-risk attitude and preference heterogeneity based on the type or phrasing of the risk attribute, we find that numeracy explained heterogeneity in the study in which risks were presented using percent, whereas literacy explained heterogeneity in the study where some risk attributes were phrased using percent and some using words.

A strength of this study is that it is among the first to research health-risk attitude as an individual characteristic underlying heterogeneity in health preferences and thereby responds to the call for this type of research.[12,13,22] The case studies provide a cross-European comparison in 3 different health contexts with varying degrees of risk and study population leading to an increased generalizability of the results. Nevertheless, the differences in samples also make it harder to identify the source of similarities and differences in results between the studies. Given that secondary data were used for the current study, comparability across the studies is limited. In future research, it would be interesting to set up studies with the specific aim to compare the impact of health-risk attitude across different populations and risk attributes. It should also be noted that it is unclear whether respondents' level of perceived riskiness of the attributes is in line with what was determined by the researchers. Given that risk perception and risk behavior are not always aligned,[15] we recommend future research in this area to also elicit respondents' risk perception at an early stage of DCE development. Furthermore, this research focused on improving model fit and model interpretations from the perspective of internal validity. Given the mixed evidence regarding the predictive ability of survey-based measures of risk attitude,[17,18,38] it would be interesting to also study whether and how health-risk attitude and heterogeneity of health preferences are related from the perspective of external validity and individual-level prediction accuracy, for example, as in de Bekker-Grob et al.[43]

In conclusion, our study did not find evidence that health-risk attitude as measured by the HRAS-13 distinguishes people between classes. Nevertheless, we did find evidence that the HRAS-13 can distinguish people's preferences for risk attributes within classes. This phenomenon was more pronounced in the patient samples than in the general population sample. Furthermore, we found that preference heterogeneity is affected by numeracy and health literacy. These results warrant the relevance of further research into preference heterogeneity beyond class membership, a different measure of health-risk attitude, and the communication of risks.

Supplemental Materials

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REFERENCES

1. Timmermans DR. What clinicians can offer: assessing and communicating probabilities for individual patient decision making. *Horm Res*. 1999;51(suppl 1):58–66.
2. Austin JC, Hippman C, Honer WG. Descriptive and numeric estimation of risk for psychotic disorders among affected individuals and relatives: implications for clinical practice. *Psychiatry Res*. 2012;196(1):52–56.
3. Montgomery AA, Fahey T. How do patients' treatment preferences compare with those of clinicians? *Qual Health Care*. 2001;10(suppl 1):i39–i43.
4. Rosen AB, Tsai JS, Downs SM. Variations in risk attitude across race, gender, and education. *Med Decis Making*. 2003;23(6):511–517.
5. Cher DJ, Miyamoto J, Lenert LA. Incorporating risk attitude into Markov-process decision models: importance for individual decision making. *Med Decis Making*. 1997;17(3):340–350.
6. Woodward RS, Schnitzler MA, Kvols LK. Reduced uncertainty as a diagnostic benefit: an initial assessment of somatostatic receptor scintigraphy's value in detecting distant metastases of carcinoid liver tumours. *Health Econ*. 1998;7(2):149–160.
7. Dieteren CM, Brouwer WBF, van Exel J. How do combinations of unhealthy behaviors relate to attitudinal factors and subjective health among the adult population in The Netherlands? [published correction appears in *BMC Public Health*. 2020;20(1):1808]. *BMC Public Health*. 2020;20(1):441.
8. Himmler S, van Exel J, Brouwer W. Did the COVID-19 pandemic change the willingness to pay for an early warning system for infectious diseases in Europe? *Eur J Health Econ*. 2022;23(1):81–94.
9. Barfoed BL, Paulsen MS, Christensen PM, et al. Associations between patients' risk attitude and their adherence to statin treatment – a population based questionnaire and register study. *BMC Fam Pract*. 2016;17(1):28.
10. Ostermann J, Brown DS, de Bekker-Grob EW, Mühlbacher AC, Reed SD. Preferences for health interventions: improving uptake, adherence, and efficiency. *Patient*. 2017;10(4):511–514.
11. Whitty JA, Fraenkel L, Saigal CS, Groothuis-Oudshoorn CGM, Regier DA, Marshall DA. Assessment of individual patient preferences to inform clinical practice. *Patient*. 2017;10(4):519–521.
12. Russo S, Monzani D, Pinto CA, et al. Taking into account patient preferences: a consensus study on the assessment of psychological dimensions within patient preference studies. *Patient Prefer Adherence*. 2021;15:1331–1345.
13. Russo S, Jongerius C, Faccio F, et al. Understanding patients' preferences: a systematic review of psychological instruments used in patients' preference and decision studies. *Value Health*. 2019;22(4):491–501.
14. Prosser LA, Wittenberg E. Do risk attitudes differ across domains and respondent types? *Med Decis Making*. 2007;27(3):281–287.
15. Weber EU, Blais A-R, Betz NE. A domain-specific risk-attitude scale: measuring risk perceptions and risk behaviors. *J Behav Decis Making*. 2002;15(4):263–290.
16. Huls SPI, van Osch SMC, Brouwer WBF, van Exel J, Stiggelbout AM. Psychometric evaluation of the Health-Risk Attitude Scale (HRAS-13): assessing the reliability, dimensionality and validity in the general population and a patient population. *Psychol Health*. 2022;37:34–50.
17. Zhang DC, Highhouse S, Nye CD. Development and validation of the general risk propensity scale (GRiPS). *J Behav Decis Making*. 2019;32(2):152–167.
18. Charness G, Garcia T, Offerman T, Villeval MC. Do measures of risk attitude in the laboratory predict behavior under risk in and outside of the laboratory? *J Risk Uncertain*. 2020;60:99–123.
19. Soekhai V, de Bekker-Grob EW, Ellis AR, Vass CM. Discrete choice experiments in health economics: past, present and future. *Pharmacoeconomics*. 2019;37(2):201–226.
20. Patient preference information - voluntary submission, review in premarket approval applications, humanitarian device exemption applications, and de novo requests, and inclusion in decision summaries and device labeling. Food and Drug Administration, Center for Devices and Radiological Health. https://www.fda.gov/regulatory-information/search-fda-guidance-documents/patient-preference-information-voluntary-submission-review-premarket-approval-applications. Accessed August 11, 2021.
21. The patient's voice in the evaluation of medicines. European Medicines Agency. https://www.ema.europa.eu/en/documents/report/report-workshop-patients-voice-evaluation-medicines_en.pdf. Accessed August 11, 2021.
22. Harrison M, Rigby D, Vass C, Flynn T, Louviere J, Payne K. Risk as an attribute in discrete choice experiments: a systematic review of the literature. *Patient*. 2014;7(2):151–170.
23. Tsuge T, Kishimoto A, Takeuchi K. A choice experiment approach to the valuation of mortality. *J Risk Uncertain*. 2005;31(1):73–95.
24. Huls SPI, Whichello CL, van Exel J, Uyl-de Groot CA, de Bekker-Grob EW. What is next for patient preferences in health technology assessment? A systematic review of the challenges. *Value Health*. 2019;22(11):1318–1328.
25. Whichello C, van Overbeeke E, Janssens R, et al. Factors and situations affecting the value of patient preference studies: semi-structured interviews in Europe and the US. *Front Pharmacol*. 2019;10:1009.

26. Vass C, Rigby D, Payne K. "I Was Trying to Do the Maths": exploring the impact of risk communication in discrete choice experiments. *Patient*. 2019;12(1):113–123.
27. Nguyen F, Carrere MO, Moumjid N. Framing effects of risk communication in health-related decision making; learning from a discrete choice experiment. Report no.: ID 1513293. Social Science Research Network. https://papers.ssrn.com/abstract=1513293. Accessed March 2, 2022.
28. de Bekker-Grob EW, Swait JD, Kassahun HT, et al. Are healthcare choices predictable? The impact of discrete choice experiment designs and models. *Value Health*. 2019;22(9):1050–1062.
29. Veldwijk J, van der Heide I, Rademakers J, et al. Preferences for vaccination: does health literacy make a difference? *Med Decis Making*. 2015;35(8):948–958.
30. Visser LA, Huls SPI, Uyl-de Groot CA, de Bekker-Grob EW, Redekop WK. An implantable device to treat multiple sclerosis: a discrete choice experiment on patient preferences in three European countries. *J Neurol Sci*. 2021;248:117587.
31. Ancillotti M, Eriksson S, Andersson DI, Godskesen T, Nihlén Fahlquist J, Veldwijk J. Preferences regarding antibiotic treatment and the role of antibiotic resistance: a discrete choice experiment. *Int J Antimicrob Agents*. 2020;56(6):106198.
32. Arslan IG, Huls SPI, Bekker-Grob EW de, et al. Patients', healthcare providers', and insurance company employees' preferences for knee and hip osteoarthritis care: a discrete choice experiment. *Osteoarthritis Cartilage*. 2020;28(10):1316–1324.
33. Anderhub V, Güth W, Gneezy U, Sonsino D. On the interaction of risk and time preferences: an experimental study. *Ger Econ Rev*. 2001;2(3):239–253.
34. Gafni A, Torrance GW. Risk attitude and time preference in health. *Manage Sci*. 1984;30(4):440–451.
35. Conroy RM, Smyth O, Siriwardena R, Fernandes P. Health anxiety and characteristics of self-initiated general practitioner consultations. *J Psychosom Res*. 1999;46(1):45–50.
36. Charpentier CJ, Aylward J, Roiser JP, Robinson OJ. Enhanced risk aversion, but not loss aversion, in unmedicated pathological anxiety. *Biol Psychiatry*. 2017;81(12):1014–1022.
37. Ngene user manual. ChoiceMetrics. http://www.choice-metrics.com/NgeneManual120.pdf. Accessed August 26, 2021.
38. Islam A, Smyth R, Tan HA, Wang LC. Survey measures versus incentivized measures of risk preferences: evidence from sex workers' risky sexual transactions. *Soc Sci Med*. 2019;238:112497.
39. European qualifications framework (EQF). Cedefop. https://www.cedefop.europa.eu/en/events-and-projects/projects/european-qualifications-framework-eqf. Accessed July 29, 2021.
40. NLQF-niveaus. Netherlands qualification framework (NLQF). https://www.nlqf.nl/nlqf-niveaus. Accessed July 29, 2021.
41. Opleidingsniveau. Central Bureau of Statistics, Centraal Bureau Voor de Statistiek. https://www.cbs.nl/nl-nl/nieuws/2019/33/verschil-levensverwachting-hoog-en-laagopgeleid-groeit/opleidingsniveau. Accessed July 29, 2021.
42. Ishikawa H, Nomura K, Sato M, Yano E. Developing a measure of communicative and critical health literacy: a pilot study of Japanese office workers. *Health Promot Int*. 2008;23(3):269–274.
43. de Bekker-Grob EW, Donkers B, Bliemer MCJ, Veldwijk J, Swait JD. Can healthcare choice be predicted using stated preference data? *Soc Sci Med*. 2020;246:112736.
44. de Bekker-Grob EW, Donkers B, Veldwijk J, et al. What factors influence non-participation most in colorectal cancer screening? A discrete choice experiment. *Patient*. 2021;14(2):269–281.
45. van der Vaart R, Drossaert CHC, Taal E, et al. Validation of the Dutch functional, communicative and critical health literacy scales. *Patient Educ Couns*. 2012;89(1):82–88.
46. Wångdahl JM, Mårtensson LI. The communicative and critical health literacy scale– Swedish version. *Scand J Public Health*. 2014;42(1):25–31.
47. McNaughton CD, Cavanaugh KL, Kripalani S, Rothman RL, Wallston KA. Validation of a short, 3-item version of the subjective numeracy scale. *Med Decis Making*. 2015;35(8):932–936.
48. Hess S. Latent class structures: taste heterogeneity and beyond. In: *Handbook of Choice Modelling*. Cheltenham, United Kingdom: Edward Elgar Publishing; 2014:311–330.
49. Greene WH, Hensher DA. A latent class model for discrete choice analysis: contrasts with mixed logit. *Transp Res B Methodol*. 2003;37(8):681–698.
50. Swait J. A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. *J Retail Consum Serv*. 1994;1(2):77–89.
51. Bansback N, Harrison M, Sadatsafavi M, Stiggelbout A, Whitehurst DGT. Attitude to health risk in the Canadian population: a cross-sectional survey. *CMAJ Open*. 2016;4(2):E284–E291.
52. Wakker P, Deneffe D. Eliciting von Neumann-Morgenstern utilities when probabilities are distorted or unknown. *Manag Sci*. 1996;42(8):1131–1150.
53. Bleichrodt H, Pinto JL, Wakker PP. Making descriptive use of prospect theory to improve the prescriptive use of expected utility. *Manag Sci*. 2001;47(11):1498–1514.
54. Bleichrodt H, Abellan-Perpiñan JM, Pinto-Prades JL, Mendez-Martinez I. Resolving inconsistencies in utility measurement under risk: tests of generalizations of expected utility. *Manage Sci*. 2007;53(3):469–482.
55. Lejuez CW, Read JP, Kahler CW, et al. Evaluation of a behavioral measure of risk taking: the balloon analogue risk task (BART). *J Exp Psychol Appl*. 2002;8(2):75–84.
56. Peters E, Hart PS, Fraenkel L. Informing patients: the influence of numeracy, framing, and format of side effect information on risk perceptions. *Med Decis Making*. 2011;31(3):432–436.