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Preference-Based Assessment

Combining Individual-Level Discrete Choice Experiment Estimates and Costs to Inform Health Care Management Decisions about Customized Care: The Case of Follow-Up Strategies after Breast Cancer Treatment

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ABSTRACT

Objective: Customized care can be beneficial for patients when preferences for health care programs are heterogeneous. Yet, there is little guidance on how individual-specific preferences and cost data can be combined to inform health care decisions about customized care. Therefore, we propose a discrete choice experiment–based approach that illustrates how to analyze the cost-effectiveness of customized (and noncustomized) care programs to provide information for hospital managers. **Methods:** We exploit the fact that choice models make it possible to determine whether preference heterogeneity exists and to obtain individual-specific parameter estimates. We present an approach of how to combine these individual-specific parameter estimates from a random parameter model (mixed logit model) with cost data to analyze the cost-effectiveness of customized care and demonstrate our method in the case of follow-up after breast cancer treatment. **Results:** We found that there is significant preference heterogeneity for all except two attributes of breast cancer treatment follow-up and that the fully customized care program leads to higher utility and lower costs than the current standardized program. Compared with the single alternative program, the fully customized care program has increased benefits and higher costs. Thus, it is necessary for health care decision makers to judge whether the use of resources for customized care is cost-effective. **Conclusions:** Decision makers should consider using the results obtained from our methodological approach when they consider implementing customized health care programs, because it may help to find ways to save costs and increase patient satisfaction.

Keywords: breast cancer, customized care, discrete choice experiment, economic evaluation, individualized care, process-related aspects of care, preference heterogeneity.

Introduction

Heterogeneity in taste is prominent in health care, for example, in variations in preferences between individuals for different treatment programs [1,2]. Furthermore, the rise of consumerism and the growth in available information through the Internet have raised patients' expectations about care and increasingly patients demand care that is more in line with their own individual preferences. This trend emphasizes the importance for health care organizations to evaluate the possibility of offering customized care (also referred to as custom-made care). *Customized care* is defined as health care that is individually tailored on a patient-by-patient basis [3]. We distinguish customized care from personalized medicine, which involves the systematic use of genetic or other information about an individual patient to select that patient's preventative and therapeutic medicine or medical intervention [4,5]. Rather, we operationalize customized care more broadly as any type of health care that offers individualized programs that reflect each patient's own preferences. This contrasts customized care with standardized care, which offers the same health care program to all patients, thereby largely ignoring differences in patients' preferences. We note that in daily health care practice intermediate approaches are often followed, for example, on the basis of patient stratification or with clinical practice guidelines that offer doctors the possibility to partially take patients' preferences into account.

Although customized care is potentially beneficial to patients, it is not commonly implemented in practice, possibly because of the fear for high additional communication, cognition, coordination, and capability costs (i.e., the fixed cost in having a capability available, the equivalent of an up-front in-

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Table 1 – Attributes and attribute levels.

Attributes	Attribute levels	Explanations
Attendance at educational group program	Yes No	The educational group program consists of two group meetings of 2 h, led by a breast care nurse and a health care psychologist, in which patients (and their partners) are informed of the physical and psychosocial consequences of the disease and its treatment, and possible signs of recurrence.
Frequency of visits	Every 3 mo Every 4 mo Every 6 mo Every 12 mo	The frequency of visits determines whether a patient has scheduled follow-up visits every 3, 4, 6, or 12 mo. Regardless of the frequency, patients can always make additional appointments whenever they feel the need.
Waiting time in minutes	5 30 60 90	This is the time a patient has to wait after the set time of the appointment. This can thus be at the hospital or general practitioner's office (face-to-face contact) or at home (telephone contact).
Contact mode	Face to face Telephone	A visit (face-to-face) to a health care provider consists of a short physical examination and open discussion about general well-being and the recovery process. A telephone follow-up consists of an open discussion about general well-being and the recovery process only. If the patient or health care provider feels the need, an additional appointment (face-to-face) can be made.
Health care provider	Medical specialist Breast care nurse/ nurse practitioner General practitioner Breast care nurse and medical specialist	The medical specialist is (preferably) the patient's surgeon, oncologist, or radiotherapist. They may alternate. The breast care nurse is a nurse specialized in breast cancer; a nurse practitioner is a nurse with advanced medical training (master's level). They are both referred to as breast care nurse in the survey. In all cases, the last contact with the health care provider is with a medical specialist to conduct a mammography.

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vestment cost) [3]. The concept of customized care fits well with the principles of shared decision making, in which a doctor and a patient jointly come to a decision about treatment [6,7]. Customized care may potentially generate efficiency gains, because there may be circumstances in which a large proportion of individuals prefer a less costly health care program above a more expensive one. In such a case, introducing customized health care programs that better serve patients' preferences may be an option. It is of paramount importance to determine whether customized care leads to a cost-effective use of resources before it is implemented in practice. For this purpose, insights into individuals' specific health care program preferences are needed, and perhaps even more importantly, a method should be available that allows one to use these preferences in combination with corresponding cost data to inform health care decision makers (e.g., hospital managers) about customized care. To our knowledge, such a method is not available in the health care literature. Yet, when individual-specific preferences are not accurately measured, this can lead to biased utility (welfare) measures and erroneous evaluations of customized care [8,9].

Including individual-specific preferences in cost-effectiveness analysis to inform health care decision making

Traditionally, the focus of cost-effectiveness analysis has lain on identifying average costs and benefits in the population and on the identification of subgroups of patients for which a health care program may be more or less cost-effective. Research, however, has shown that it is also valuable to identify cost-effectiveness on the individual level [10–12]. Therefore, in this article we incorporate individual benefits, instead of average benefits, in cost-effectiveness analysis. More specifically, we provide a method to combine individual-specific preference data, which can flexibly include aspects of care related to health and process (i.e., nonhealth), with health care program–specific cost data to inform health care decision makers about (the cost-effectiveness of) customized care.

Our approach combines individual-specific preferences identified from a discrete choice experiment (DCE) with health care program–specific cost data. A DCE is a method based on stated preferences in which respondents are asked to choose between hypothetical alternatives constructed on the basis of an experimental design. A large number of DCE applications can be found in the health economics literature, and the trend shows that DCEs have been used more widely for health economics research in recent years [13,14]. Traditionally, DCEs are used to elicit patient preferences and to quantify trade-offs between alternative treatments [15–18]. Although there is growing recognition that DCEs have the potential to contribute more directly to outcome measurement for use in economic evaluations [19], the question how DCE data can be used to inform health policy [20] is still relatively unexplored. For example, McIntosh [21] proposed an initial framework for cost-benefit analysis using DCEs and McCormack et al. [22] review different types of benefit measures that can be analyzed to support health policy decisions including DCE-derived welfare estimates as one of the options. However, in these articles, the focus has been on estimating average preferences.

In contrast, we used DCE data to estimate choice models (e.g., the random parameters logit or generalized mixed logit model) that reflect individual-level preferences. Appropriate analysis of DCE data determines whether preference heterogeneity exists, and if so, individual-specific utility estimates for different health care programs can be obtained. More specifically, DCE-based choice models offer utility estimates for all attribute levels of a health care program (including health- and process-related aspects), making it possible to investigate the cost-effectiveness of a wide range of possible programs.

Thus, this article contributes to the literature by presenting a methodological approach of how to combine individual-specific DCE-based preference information with health care program–specific cost data to inform health care decision makers about the cost-effectiveness of customized care. Especially in view of

Table 2 – Utility calculations for specialist-led* face-to-face follow-up (4 times a year) and no EGP based on individual-specific DCE estimates.

Respondent	EGP	Coding	Waiting time	Coding	Telephone	Coding	Frequency	Coding	Frequency squared	Coding	Utility†
1	−0.239	0	−0.012	5	−1.398	0	1.275	4	−0.217	16	1.568‡
2	−0.708	0	−0.015	5	−0.945	0	1.725	4	−0.220	16	3.305
3	−2.419	0	−0.002	5	−0.621	0	1.334	4	−0.222	16	1.774
4	−1.176	0	−0.012	5	0.335	0	1.557	4	−0.237	16	2.376
5	−0.152	0	−0.007	5	−4.463	0	1.492	4	−0.222	16	2.381
6	−2.393	0	−0.004	5	−1.351	0	1.537	4	−0.225	16	2.528
7	−1.091	0	−0.003	5	−0.122	0	1.331	4	−0.228	16	1.661
8	−1.402	0	−0.009	5	−2.731	0	1.948	4	−0.220	16	4.227
9	−1.850	0	−0.007	5	−2.772	0	1.763	4	−0.220	16	3.497
10§	−1.138	0	−0.000	5	−3.077	0	1.394	4	−0.221	16	2.04
											25.357‖

DCE, discrete choice experiment; EGP, educational group program.

* Note that the medical specialist is used as reference category in our calculations; therefore, the type of health care provider is not shown in the table.

† There is no standardized scale on which utilities are measured in DCEs across studies. Therefore, they are not scaled between 0 and 1 and cannot be compared over studies.

‡ The total utility of respondent 1 is calculated as follows: $[(-0.239 \times 0) + (-0.012 \times 5) + (-1.398 \times 0) + (1.275 \times 4) + (-0.217 \times 16)] = 1.568$.

§ For practical reasons, calculations for only 10 respondents are illustrated in this table.

‖ The total utility is calculated by summing the utilities of all individuals (i.e., 1.568 + 3.305 + . . . + . . . = 25.357).

its rising importance and the possibility to offer customized care, the introduction of such an approach is both relevant and topical [23].

We demonstrate our method for the case of follow-up programs after breast cancer treatment. Patients were found to have heterogeneous preferences for this type of care [24]. Individual preferences for breast cancer follow-up [24] and associated follow-up program– specific costs [25] were combined to illustrate how they can guide decisions on implementing customized care. The analysis is based on process-related aspects of follow-up (e.g., the frequency of follow-up visits and type of health care professional) and the costs associated with several follow-up strategies recently reported in the MaCare trial performed in The Netherlands. The DCE focused on process-related aspects of care (see Table 1) because no differences were found in health benefits between the different follow-up programs [26]. The proposed principles can, however, be applied to health care programs that (also) have different health consequences.

The remainder of this article is structured as follows. First, we outline the proposed DCE-based approach. To do so, we provide a brief overview of the random utility model we use. This is followed by a description of how to combine individual-specific DCE estimates with follow-up program–specific costs. Next, we present analyses in an application in which we report the cost-effectiveness of different breast cancer follow-up programs as well as a (fully) customized care program relative to the current standardized program and show how the results of our approach can help hospital decision makers in evaluating the implementation of customized care. Note that effectiveness is measured in terms of utility in this article. We close with a discussion of our findings and provide suggestions for future research.

The Individual-Level Preference Model

We obtain individual-level estimates for attributes of follow-up care by means of a random parameter logit (RPL) model (also known as the mixed logit model) based on DCE data. The model is based on random utility theory, which assumes that an individual n's utility for choice alternative j in observation t (U_{njt}) consists of a systematic utility component (V_{nj}), an error scale parameter (λ), and a random component (ε_{njt}).

$$U_{njt} = \lambda V_{nj} + \varepsilon_{njt} \quad (1)$$

To further specify the individual-level differences in preferences, the model is extended by explicitly allowing for individual-specific variations in taste:

$$V_{nj} = \lambda \beta_n{}' x_j$$
$$\beta_n = \beta + \nu_n \quad (2)$$

Here the utility component is described in terms of the vector of observed attributes for the health care program ($\mathbf{x_j}$) and an individual-specific vector of preference coefficients ($\boldsymbol{\beta_n}$). The preference vector is separated in a mean preference component shared by all individuals ($\boldsymbol{\beta}$) and an individual-specific error component that captures differences in individuals' taste (ν_n). The individual-specific error components are assumed to be independently normally distributed and are allowed to have different variances. In this way, the RPL model takes into account variations in respondents' taste (i.e., preference heterogeneity). It is worth noting that this model provides unbiased individual-level estimates only if the correct distributions are used in modeling preferences.

The probability that alternative j is chosen, given that a respondent has to choose between alternatives j and i, is specified as follows:

$$P_{njt} = \Pr(U_{njt} > U_{nit}) = \Pr(\lambda V_{nj} + \varepsilon_{njt} > \lambda V_{ni} + \varepsilon_{nit}) =$$
$$\Pr(\lambda V_{nj} - \lambda V_{ni} > \varepsilon_{nit} - \varepsilon_{njt}) \quad (3)$$

If we assume that the error terms (ε_{njt}, ε_{nit}) are identically and independently Gumbel distributed, and the error scale parameter

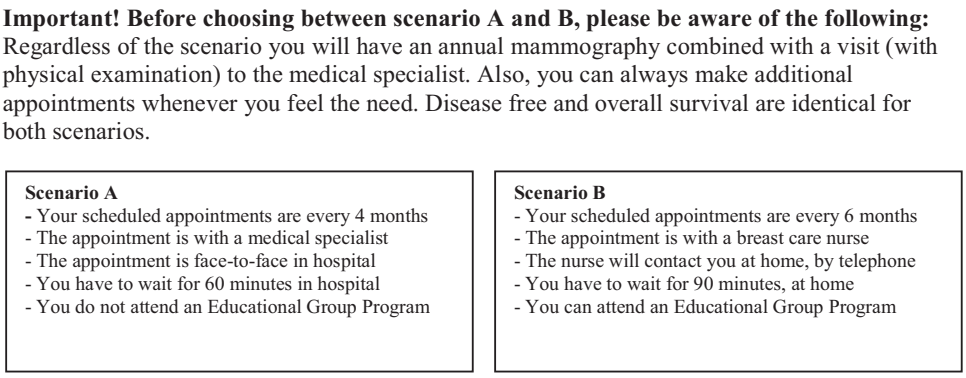

Fig. 1 – Example of a choice task. Reprinted from Acta Oncologica, 49(3), Kimman ML, Dellaert BGC, Boersma LI, et al, Follow-up after treatment for breast cancer: one strategy fits all? An investigation of patient preferences using a discrete choice experiment, 328–337, 2010, with permission from Informa Healthcare.

is set to 1, this results in the standard binary logit specification for any given individual n:

$$P_{nj} = \exp(V_{nj})/[\exp(V_{nj}) + \exp(V_{ni})] \quad (4)$$

A major advantage of the RPL model is that posterior estimates for each individual's preference parameters for the attributes of a health care program can be obtained on the basis of the individual's observed choices and the random parameter distribution estimates [27,28]. This property is shared with the recently introduced generalized multinomial logit model [29], but it is different from, for example, the traditional multinomial logit model that estimates average population parameters for the attributes of a health care program or the latent class analysis logit model that allows for heterogeneity between patients at the segment but not at the individual level [30].

The individual-specific preference parameter estimates from the RPL model can be used to calculate—for each individual—utilities for the full range of possible follow-up programs, including each individual's most preferred one. Assuming that utilities are all measured on the same utility scale, the total utility for the sample can be calculated for each possible follow-up program. This can be done by adding the individual-specific utilities of a follow-up program for all individuals in the sample (see Table 2 for an illustration of these calculations for 10 patients of our sample).

Combining individual-specific DCE estimates and costs

Once the utility of a specific follow-up program is calculated, this utility can be combined with cost data for the specific program j provided to each individual n (C_{nj}) to allow for comparisons across programs. A cost-utility comparison with other (noncustomized) health care programs can be made to analyze whether offering a customized program leads to greater utility and/or lower costs for the total sample. For example, if a sufficiently large number of patients choose a less costly follow-up program in the customization process compared with the standardized follow-up program, this leads to both higher total utility and lower costs. Finally, to inform hospital decision makers about the cost-effectiveness of customized care, the incremental utility and costs of each follow-up strategy have to be compared with the incremental utilities and costs of other strategies or current practice to decide which strategy to implement. In practice, it is important for a decision maker to know whether a customized follow-up program dominates the standardized program and other programs to make an informed decision about implementing customized care.

Implementing customized care or not: two approaches of total utility calculation

The calculation of the total utility of the sample depends on the approach that is taken by the management to implement the customization program. First, customization can be implemented by assigning patients directly to their predicted (individually) most preferred program. This approach is in line with how treatments are commonly assigned in health care, when doctors aim to offer patients treatments on the basis of the expected benefit for the patient. In this case, by using the RPL estimates of each patient's individual-level utilities, one can first calculate the utility for each patient's most preferred program and then add up the utilities across all patients of their most preferred program to obtain the total utility. We use this approach in our application as it is most in line with current practice in most hospitals. A prerequisite for this approach is that individual-level preference estimates are available as is the case in the proposed DCE-based approach.

An alternative approach to customization would be to allow patients to choose their own most preferred program from a set of health program modules (e.g., after providing them with a brief description of each program). This approach is more in line with the way customization is implemented, for example, in most consumer goods markets, where consumers can compose their own products by selecting their most preferred options for each set of available modules. A critical distinction between this alternative approach and the proposed previous one is in how the total utility of a health care program needs to be calculated. In particular, while in the first approach it is known with certainty what treatment is assigned to which patient (because the doctor assigns each patient), in the second approach the actual choice that the patient will make is uncertain and needs to be predicted by the researcher (on the basis of available preference data). Hence, there is an inherent uncertainty about which program the patient will actually choose [18]. In this latter case, the utility of each program needs to be weighted in the analysis by the probability that the program is chosen by each patient to

Table 3 – Cost calculations of follow-up strategy components from a hospital perspective.

Health care provider	Contact mode	Yearly salary	Average yearly working hours	Hours of patient time	Employers' contributions (%)	Overhead costs (%)	Length of follow-up contact (min)	Direct material and direct personnel costs	Price index number	Costs (€)
Breast care nurse	Telephone	3618 × 12	1540	–	39	45	20	–	1.083	20.51
Breast care nurse	Face to face	3618 × 12	1540	–	39	45	20	41	1.083	64.92
Medical specialist	Telephone	8677 × 12	–	1470	35	45	15	–	1.083	37.54
Medical specialist	Face to face	8677 × 12	–	1470	35	45	15	41	1.083	81.94

calculate the total utility of a customized program (e.g., this implies that even relatively less attractive programs are assigned a small probability of being selected in the model because of the error term in the patient utility model).

Methods: An Application to the Case of Follow-Up Strategies after Breast Cancer Treatment

In this section, we conduct the proposed analysis to investigate whether offering customized programs can be cost-effective in the case of breast cancer follow-up care.

Data and analysis

Experimental design, survey, and data

Details of the DCE that we used are described elsewhere [24] and we provide only a brief overview. Attributes and attribute levels (Table 1) were based on a review of the literature [31], new local policy initiatives [26], and expert opinions [32]. An orthogonal fractional factorial design with 32 hypothetical choice tasks was created from a full factorial (256 scenarios). Two surveys, each presenting 16 choice tasks to a patient, were used. All respondents were randomly assigned to one of the two surveys, and in the analysis there was no significant main effect of survey version. The survey started with a short introduction of the purpose and effectiveness of follow-up after breast cancer treatment followed by a description of the attributes, their levels, and the choice tasks (Fig. 1). The data collection took place between May and July 2008. In total 331 patients (from five hospitals) completed the DCE (response rate of 59%). Their average age was 58 years (ranging from 34 to 83 years), and the mean time since finalizing breast cancer treatment was 14 months (ranging from 2 to 24 months).

Model

We analyzed the DCE data by estimating the proposed RPL model by using 500 Halton draws in NLOGIT 3.0 (Econometric Software, Inc.). Because the main aim of our study was to explore the cost-effectiveness of introducing customized care when there is preference heterogeneity, we deemed it important to freely allow respondents to have negative or positive preferences for an attribute level in our model. Therefore, in the analysis, results are based on normal distributions for the random parameters. The utility function of our model is specified as follows (the error scale parameter [λ] is fixed to 1 for identification):

$$U_{njt} = (\beta_1 + \nu_{1n})EGP_j + (\beta_2 + \nu_{2n})FREQ_j + (\beta_3 + \nu_{3n})(FREQ_j)^2 + (\beta_4 + \nu_{4n})WT_j + (\beta_5 + \nu_{5n})TEL_j + (\beta_6 + \nu_{6n})BCN_j + (\beta_7 + \nu_{7n})GP_j + (\beta_8 + \nu_{8n})MS/BCN_j + \varepsilon_{njt} \quad (5)$$

where U_{njt} is individual n's utility associated with a specific follow-up scenario j in choice observation t, $\beta_1$to β_8 are the mean parameter estimates of the model that indicate the preference for each attribute as it occurs in follow-up scenario j. ν_{1n} to ν_{8n} correspond to the individual-specific error terms for every preference parameter. EGP is a dummy variable for educational group program attendance or not. FREQ and FREQ^2 represent the frequency and squared frequency, respectively, of follow-up visits in a year. WT represents the waiting time during follow-up interaction with the hospital. TEL is a dummy variable for telephone versus face-to-face contact and BCN (breast care nurse), GP (general practitioner), and MS/BCN (i.e., alternating between medical specialist and breast care nurse) are dummy variables reflecting the different health care providers of follow-up, with medical specialist–only visits as a base level. The base levels reflect current practice levels

Table 4 – Cost calculations of follow-up strategies from a hospital perspective.

Follow-up program	Costs (€)						Total cost per patient (€)
	Nurse-led telephone follow-up	Nurse-led face-to-face follow-up	Specialist-led telephone follow-up	Specialist-led face-to-face follow-up	Mammography	Educational group program (EGP)	
Cheapest single alternative ("C"): 2 × nurse-led telephone follow-up and 1 specialist-led face-to-face visit, no EGP	2 × 20.51	0	0	1 × 81.94	79.75	0	202.71
Single alternative ("A"): 3 × specialist-led face-to-face visits, no EGP	0	0	0	3 × 81.94	79.75	0	325.75
Standardized ("S"): 4 × specialist-led face-to-face visits, no EGP	0	0	0	4 × 81.94	79.75	0	407.51
Customized program ("4M")	Variable	Variable	Variable	Variable	79.75	Variable	(452.04)*
Customized program ("8M+")	Variable	Variable	Variable	Variable	79.75	Variable	(409.28)*
Fully customized ("FC") program	Variable	Variable	Variable	Variable	79.75	Variable	(375.44)*

* The average costs per patient for the customized programs 4M, 8M+, and FC are based on patient preferences and cannot be determined beforehand (see also the "variable" notations in the figure). To calculate these costs, we have to use individual-specific preferences from the discrete choice experiment. The costs resulting from this analysis are placed between parentheses. For example, the total per patient cost for the (partially) customized program "4M" (€452.04) is calculated by summing the costs of each patient's preferred program (from the, in this case, four programs offered) and dividing the resulting total costs by the number of patients in the sample.

Table 5 – Random parameter model estimations.

Variable	β	Standard error	Significance level
Random parameters (β_n)			
TEL Telephone contact mode	−2.15	.12	.00
EGP Educational group program	−.14	.08	.08
WT Waiting time	−.01	.00	.00
FREQ Frequency	1.56	.19	.00
$FREQ^2$ Frequency squared	−.22	.04	.00
BCN Breast care nurse	−.47	.10	.00
GP General practitioner	−2.24	.16	.00
MS/BCN Medical specialist and breast care nurse	.13	.09	.16
SD estimates/ heterogeneity component (ν_n)			
TEL Telephone contact mode	1.62	.12	.00
EGP Educational group program	1.20	.10	.00
WT Waiting time	.01	.00	.00
FREQ Frequency	.45	.05	.00
$FREQ^2$ Frequency squared	.01	.02	.47
BCN Breast care nurse	1.08	.12	.00
GP General practitioner	1.83	.15	.00
MS/BCN Medical specialist and breast care nurse	.31	.20	.12

in the Netherlands, and ε_{njt} is an error term that captures any remaining unobserved error.

Follow-up program costs

The costs of (alternative) follow-up programs (Tables 3 and 4) were based on a hospital management perspective and the program to which each individual patient was assigned. Therefore, we included only those costs that were related to the attributes used in the DCE that are relevant in cases in which hospital managers rather than health care policymakers wish to evaluate whether or not to offer customized care for breast cancer follow-up. The total costs for each specific follow-up program are made up of the costs per program component, as defined by the attributes and their levels. Cost prices were primarily obtained from the Dutch governmental manual for health care cost analysis [33]. Costs for hospital visits were based on cost prices for academic hospitals. All cost prices were converted to 2008 euros by means of price index numbers [34]. The time horizon used was 12 months, consistent with the time frame of the follow-up scenarios in the DCE. For a detailed

overview and precise description of the cost-price calculations, we refer to Tables 3 and 4, and Appendix A in the Supplemental Material found at http://dx.doi.org/10.1016/j.jval.2012.04.007.

Results

Model estimates

The model estimation results (Table 5) show significant mean preference parameters for all but two of the attributes and with signs as expected. Significant preference heterogeneity for the attributes of follow-up is evidenced by the significant estimates for the SDs for the individual-specific error terms (ν_n) for all but two of the preference parameters (i.e., FREQ2 and MS/BCN). These estimates show that the size of the preference heterogeneity component is relatively large, leading to a number of different follow-up programs being most preferred by different groups of patients. For example, about 21% of patients prefer a program that offers 3 times specialist-/nurse-led face-to-face follow-up in a year and no EGP (see Fig. 2). Therefore, it is especially relevant to investigate the cost-effectives of customized follow-up strategies compared with standardized follow-up and other follow-up strategies.

A key element in the use of RPL modeling is the assumption regarding the distribution of each of the random parameters. In our analysis, all parameters were assigned as normally distributed random parameters to allow for a high flexibility in possible heterogeneity. To ensure that our results were robust for distributions, however, we also performed a secondary analysis, in which the attribute levels general practitioner, telephone contact, and frequency were assigned a lognormal distribution (because of the observed relatively limited heterogeneity in preferences in these attributes). This led to highly similar effects and only a marginal improvement in model fit but restricted respondents' preferences to be either all positive or all negative for a given attribute level. Given the only marginal improvement in fit and because the main aim of our study was to explore the cost-benefits of preference heterogeneity by introducing customization, we deemed it more appropriate to allow respondents to have either a negative preference or a positive preference for an attribute level. Therefore, we report the further policy analysis results with normal distributions for the random parameters.

Follow-up program evaluations: policy evaluations

To inform health care decision makers about the cost-effectiveness of customized care, the utility and costs of each follow-up strategy (across all patients) are compared with the utilities and costs of the other possible strategies as well as the current standardized program to decide

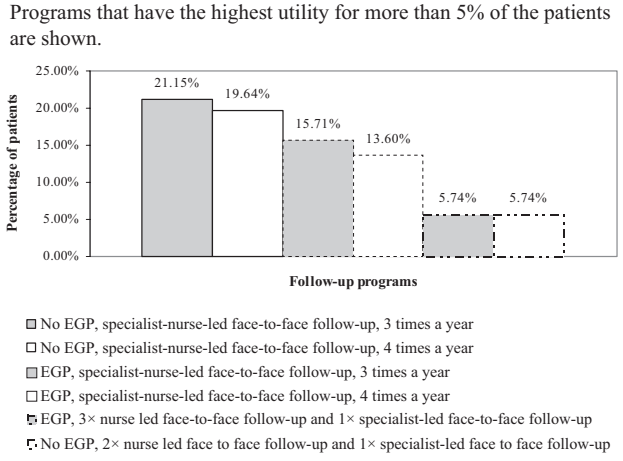

Fig. 2 – Patients' highest utility programs with full customization.

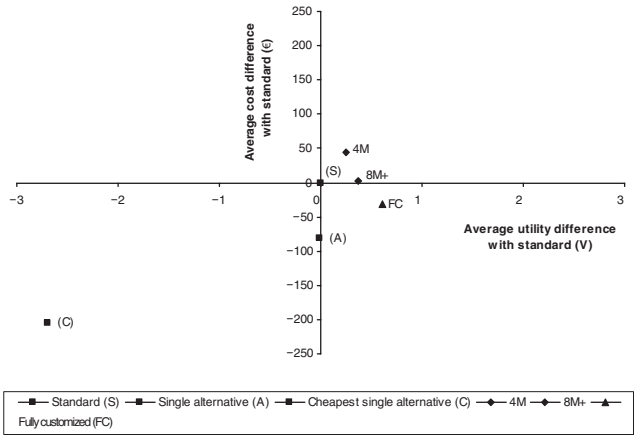

Fig. 3 – Cost-utility comparisons of follow-up programs with current standardized program.

which strategy to implement. In Figure 3 we show the evaluation results for several follow-up programs relative to the current standardized program ("S"). Note that waiting time is assumed to be constant across programs and was set at 5 minutes in the evaluations. These programs represent two "best in class" alternative programs and programs that were evaluated in the MaCare trial. They are 1) a single alternative program that leads to much lower average costs than the standard program and an approximately equal average utility level ("A"), 2) the least expensive single alternative program ("C"), 3) a strategy in which patients are assigned to their preferred follow-up program from the four programs that were evaluated in the MaCare trial ("4M"), 4) a strategy in which patients are assigned to their preferred follow-up program from the four programs of the MaCare trial or a reduced version of one of these programs with one follow-up visit less ("8M+"), and 5) a fully customized (FC) program in which all patients are assigned to their most preferred (highest utility) follow-up program ("FC"). Table 6 provides a summary description of the programs and indicates whether a program's cost and utility values are strictly dominated by other programs.

The results demonstrate that full customization of care according to patients' preferences would be a very good option in the case of follow-up after breast cancer treatment. The average utility of such a strategy is higher than that of all alternative programs, while its average costs are below that of the current standardized program, and also lower than those of programs 4M and 8M+. Thus, the FC program dominates programs S, 4M, and 8M+ (Table 6). The single alternatives A and C are not dominated by the FC program because they have lower average costs. In instances such as this, where the FC program has a higher utility and higher costs than do other programs, it is necessary for a decision maker to judge what a cost-effective use of resources is. The implementation of programs A and C may be more likely in case hospital managers are willing to trade-off a lower utility for a cost saving.

Because full customization may not be practical in all settings, we also investigate alternative follow-up programs that offer some, but fewer options (partially customized follow-up). In these alternative strategies, patients receive their preferred program from the programs that are offered by the hospital. For instance, in program "8M+," patients could get programs with a frequency of two, three, or four visits, nurse-led telephone follow-up or specialist-led face-to-face follow-up, and an EGP or not. Assigning patients to these eight follow-up programs leads to a higher average utility level and higher average costs than the current standardized follow-up program (Fig. 3).

In summary, our analysis indicates that in the case of follow-up after breast cancer treatment, customized follow-up programs can be cost-effective alternatives to a one-strategy-for-all approach, especially when current cost levels are acceptable to hospital management.

Table 6 – Cost-utility comparisons of follow-up programs.

Follow-up program label	Follow-up program description	Average follow-up program costs (€)	Average utility difference*	Average cost difference* (€)	Eliminations
Cheapest single alternative ("C")	Two × nurse-led telephone follow-up and one specialist-led face-to-face visit, no EGP	202.71	−2.69	−204.80	Nondominated
Single alternative ("A")	Three specialist-led face-to-face visits, no EGP	325.57	−0.01	−81.94	Nondominated
Standardized ("S")	Four specialist-led face-to-face visits, no EGP	407.51	0	0	Dominated by FC
Choice from MaCare programs ("4M")	A choice of the MaCare programs: Four specialist-led face-to-face visits, no EGP Three × nurse-led telephone follow-up and one specialist-led face-to-face visit, no EGP Four specialist-led face-to-face visits, EGP Three × nurse-led telephone follow-up and one specialist-led face-to-face visit, EGP	407.51 223.22 526.51 342.22 (452.04)†	0.25	44.53	Dominated by FC
Choice from MaCare programs and MaCare programs with one visit less ("8M+")	A choice of the MaCare programs + the option to have one visit less	407.51 223.22 526.51 342.22 325.57 202.71 444.57 321.71 (409.28)†	0.37	1.77	Dominated by FC
Fully customized ("FC")	Customized program for all patients based on individual patient preferences—includes all program attributes	(375.44)†	0.61	−32.07	Nondominated

EGP, educational group program.

* The current standardized program is taken as a basis for comparison.

† The average costs per patient for the customized programs 4M, 8M+, and FC are based on patient preferences and cannot be determined beforehand. To calculate these costs, we have to use individual-specific preferences from the discrete choice experiment. The costs resulting from this analysis are placed between parentheses.

Discussion

In this study, we proposed a DCE-based approach that illustrates how costs and individual-specific DCE-based preference information can be used to inform health care decision making about customized care. In practice, using our approach means that researchers do the proposed analysis on the request of decision makers (e.g., doctors or hospital managers) and that these decision makers can use the results for health policy implementation decisions.

We used a DCE-based approach for two reasons. First, the models used to estimate DCE data like the RPL model, but also the generalized multinomial logit and flexible individual-level choice models such as those proposed by Louviere et al. [35], can determine whether preference heterogeneity exists and offer a way to obtain individual-specific parameter estimates. Furthermore, these choice models offer utility estimates for all attributes of a health care program, making it possible to investigate the cost-effectiveness of a wide range of programs (i.e., it is possible to investigate not only a program that offers patients all possible attribute-level variations [FC program] but also more restricted programs that offer some, but fewer options [4M and 8M+ programs]).

In practice, our DCE approach can be helpful for hospitals that would like to know whether implementing customized care is (potentially) cost-effective and what type of program(s) can best be implemented. We offered a stepwise illustration of the approach in the context of breast cancer follow-up programs. The results for this case indicate that offering a FC follow-up program may benefit both patients and hospitals in cases in which patients have heterogeneous preferences. For example, patients benefit from customized care because of obtaining higher utility levels (i.e., receiving a more preferred follow-up program), while hospitals benefit because of cost savings and higher patient satisfaction rates. The results of the proposed methodological approach are based on the patients in the specific sample because individual-specific data are taken into account (instead of focusing on the average population level). In the next stage, when the FC program is implemented in practice, every new patient needs to be asked a small number of DCE-style questions (i.e., fewer than are necessary for the policy evaluation study) to determine that patient's individual-level preference on the estimated preference distribution. On this basis, the patient is then assigned by the medical team to his or her most preferred follow-up program.

While the approach is new to the health care literature and potentially relevant in many areas of health care decision making, there are some issues that could be addressed in future research. First, the cost calculations in this article are based on a health care management perspective, only including costs of the proposed follow-up strategy to the

hospital itself. For the purpose of illustrating the DCE-based approach, we felt that this was appropriate. For policymakers, however, there will often be other (health care costs) related to the health care program that they may wish to incorporate (e.g., visits to other health care professionals, diagnostic tests, and productivity losses). Hence, the cost calculations used in this article provided a hospital management–oriented approach, but in other health care cases these costs may be extended to cover total costs to society.

Second, the actual costs of each separate health care program component may vary between patients from the average costs used in the analysis. Therefore, it would be insightful to study possible variations in costs when analyzing the cost-effectiveness of offering customized care by using our approach. In our application, such individual costs data were not available. Future users of our approach, however, may wish to take heterogeneity in costs into account.

A third consideration for future research is to include the extent of variation around the mean utility estimates in the proposed cost-effectiveness evaluations. In this study, we did not include uncertainty around the mean estimates for each program because the uncertainty in the model is independent and identical for all individuals and independent between attributes. As a consequence, the uncertainty is identical for all programs. However, future users of our approach could allow for heteroscedasticity in this uncertainty and thus include variation in uncertainty in the evaluation of outcomes by estimating and presenting different confidence levels around the mean estimates for different alternatives and individuals.

Fourth, in clinical practice, it may be challenging to offer customized care because it may lead to loss of economies of scale or it may require substantial implementation costs. In the case of breast cancer follow-up, for example, there needs to be sufficient capacity and skills levels need to be such that the staff members are able to provide both telephone follow-up and the EGP. Customized care also requires careful documentation of the proposed strategy and good communication among patient, doctors, nurses, and other care providers involved. Future research may take these aspects into account when investigating the cost-effectiveness of customized health care programs.

Fifth, an important assumption is that the sample from which the preference data have been obtained is representative for the population of patients for whom customized follow-up will be implemented. In this study, DCE estimates were measured in a sample of women who had been treated for breast cancer and who were between 6 months and 2 years in follow-up. An advantage of using these respondents was that they provided informed "ex post" preferences for most attributes. Preference measurements for relatively unknown characteristics of a follow-up would have to rely on patient information provided in the survey and may be more uncertain [36]. A disadvantage of using an experienced sample, such as in the current study, however, may be that the preference for the follow-up program with which respondents have experience may be stronger than for other programs, for example, because of endowment effects or status quo bias [36,37].

Sixth, the utility levels in a choice model are dependent on the selected reference points in the model (e.g., the standardized follow-up program) as well as on the overall scale of the error term in the model [9]. Therefore, the comparison of cost-utility trade-offs between different studies is problematic. Furthermore, while for quality-adjusted life-year–based cost evaluations clear guidelines are established that describe the value of a quality-adjusted life-year in euros or dollars to make program comparisons possible, for utility-based evaluations such guidelines do not exist. The managerial implication of this model structure is that for utility-based cost evaluation models, hospitals and policymakers need to make decisions on a case-to-case basis on whether or not a certain utility improvement (or cost reduction) is cost-effective. This is straightforward in case one program dominates another program (e.g., full customization vs. the current standardized program) but becomes more difficult for nondominated program comparisons (e.g., the least expensive alternative program vs. the current standardized program).

A seventh limitation of our approach is that we do not take error scale heterogeneity into account [29,38–40]. Incorporating error scale heterogeneity in the preference model can correct for possible preference scale differences between individuals and may increase model fit. A critical concern, however, if error scale heterogeneity is introduced in the model is that it is nontrivial if individuals with different scales should be given equal or different weights in the aggregation of preferences. If one takes the view that the scale merely reflects differences in degree of error, one could be inclined to correct for scale differences in the aggregation of preferences. If one, however, takes the view that the scale is also a reflection of preference strength differences (i.e., as a multiplicative component of preference heterogeneity) one would wish to include scale differences in the aggregations of preferences. A possible avenue to overcome this dilemma may be through the calculation of willingness-to-pay measures (which in contrast to what was done in the current study requires a price attribute in the DCE) that can be used to express different individuals' utilities on a common monetary scale. This monetary scale can then be a basis for health care policy evaluations. We welcome future debate in this relevant area.

Eighth, in the customization approach that we propose and that is the basis for our corresponding analysis, patients are assigned to their most preferred follow-up program on the basis of their predicted (individually) most preferred program. This implies that no uncertainty occurs in the transition from model prediction to actual follow-up program assignment. It is worth to point out that in case an alternative approach to customization would be taken in which patients themselves choose their preferred program (e.g., from a set of health program modules), it would be more difficult to extrapolate from the DCE (stated preference) results to patients' actual program choices (revealed preference). One important reason for this difference is that it is likely that there would be differences in the error scale factor in the stated preference versus revealed preference data, which implies that choice frequencies predicted from the DCE may deviate from those that would be observed in patients' real-world choices. Thus, a promising line for future research would be to investigate how best to design the interaction between patients and physicians in case of customized care and what the effects of different interaction designs will be on how to predict patient choice outcomes.

Ninth, we can provide some suggestions for future research that are not specifically based on the proposed approach but that are more related to the specific case that was studied. Here, even though the instructions told participants to consider each program as equally efficacious, it is possible that some of the expressed preferences (such as more frequent follow-up) may be due to indirect preferences for greater efficacy rather than a true preference for more frequent contact. Future researchers could overcome these problems by using additional test questions that address and clarify the presence of equal efficacy in case of less frequent visits. Also, the use of more flexible experimental designs [35] in future use of our approach could enhance the efficiency and accuracy of DCE-based preference measurement. Here, we refer to recent developments in experimental design theory that allow for a greater integration of heterogeneity in preferences in the structure of experimental designs [41]. Another possibility to deal with this issue is to use a design that is not split into blocks (i.e., a design that offers every single patient exactly the same choice sets) but that would require each patient to respond to a greater number of questions.

Finally, an important conceptual issue is that although patients clearly value both health outcomes and process-related aspects of care [15,16], it remains an open question to what extent process aspects of care (i.e., non–health-related aspects of care) should be covered by health budgets. In the proposed approach we take a patient-centered perspective and allow for process costs to enter into the spending of a hospital's health care budget because the outcomes are expressed in terms of patient utility. An alternative, more strictly health-oriented cost-effectiveness approach could choose to focus strictly on health-

related costs and health benefits and exclude any process-related aspects of breast cancer follow-up programs.

In summary, we have provided the reader with a DCE-based approach that combines individual-specific preferences and costs to answer the question whether customized care is cost-effective compared with a base level (here current practice), and if so, what type of customized program can best be implemented in practice (i.e., a partially or fully customized program). While the emphasis of our approach lies on preference measurement for process-related aspects of care, this approach could also be applied to investigate patient preferences for health-related aspects of care in cases in which there are differences in health outcomes between health care programs. Many DCEs also incorporate health outcomes (e.g., life-years gained by the program and improved quality of life), and patients may wish to trade-off some health benefits for a better process of care. We plan to study this integration in future research. Given the strong dominance of health outcomes in health care decision making, however, we believe that the present approach may be particularly useful when hospitals have the option to offer several care programs to the patient that are not expected to directly influence health outcomes but that are likely to affect patient satisfaction and have financial implications.

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Supplemental Materials

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