A user-customizable hybrid personalization for preventive screening

Highlights

- We propose a user-adjustable, two-stage framework for targeted medical decision-making process, by using patients' descriptors to match new patients, as appropriate, to groups that predict the patient's stability analysis of preferences.
- We apply our approach to a data set of patients' preferences for colorectal cancer screening options. Incorporating patients' preferences may increase the likelihood that the patient will pursue the selected option.
- By understanding the characteristics of the changes in preferences for the procedures considered, we can determine if a group-level customization or an individualized analysis is more appropriate for a new patient.

ABSTRACT

Targeted medical decision-making is a current strategy for addressing the heterogeneity in the patient population, especially when patients' preferences are included in the decision-making process. In this paper, we propose a user-customizable hybrid framework that can be adjusted at the patient group level to target a medical decision process. Our framework provides a flexible design, capable of balancing the gain from the reduction of provider time against the cost of prediction inaccuracy resulting from group customization. The framework combines a descriptive process, used to group the patients based on preference-based subjective features, with a predictive process, which uses objective features to match a new patient with a group. We illustrate our approach by applying it to a colorectal cancer screening problem. The provider chooses what level of trade-off is appropriate, as a function of the acceptable error level. The group customization process allows decision makers to better allocate scarce resources, by potentially shortening the time-consuming process of modelling patients' preferences using individualized stability analysis.

Keywords (3-6): user-customizable hybrid personalized screening; Analytic Hierarchy Process (AHP); stability analysis; machine learning

1. Introduction

Interest in targeted medical decision-making approaches has increased, as both healthcare providers and researchers realize that a "one-measure-fits-all" approach cannot accommodate the heterogeneity in the patient population. Despite that heterogeneity, empirical evidence supports the idea that considering patients' preferences for different options may provide a basis for grouping patients.

We propose a user-adjustable, two-stage framework for targeted medical decision-making process, by using patients' descriptors to match new patients, as appropriate, to groups that predict the patient's stability analysis of preferences. Our customization approach, using group-level targeting, is a time-efficient alternative to personalization for all patients, which may be uneconomical in practice. We provide information the decision-maker can use to choose a desired level of customization, by trading-off the benefit of each level of customization against the cost of selecting it.

For illustration, we apply our approach to a data set of patients' preferences for colorectal cancer screening options. Incorporating patients' preferences may increase the likelihood that the patient will pursue the selected option. Understanding how stable the preferences are to changes in the importance of the criteria weights used in the decision-making process provides insight into the evolution of patients' preferences over time. Stability analysis of preferences refers to how the criteria weights might be changed so as to shift the final decision from one most-preferred alternative to another. By understanding the characteristics of the changes in preferences for the procedures considered, we can determine if a group-level customization or an individualized analysis is more appropriate for a new patient.

2. Literature Review

Personalized medicine offers to every patient the same level of attention (Hopp et al, 2018; Kumar et al, 2018). Eliciting the patients' preferences helps the healthcare provider understand patient's personal restrictions and the reason for seeking help (Lehman, 2017; Mulley et al, 2012). As personalization is seen as an important aspect of medical care (Stephens, 2018), identifying groups of patients who have sufficiently similar preferences across screening/treatment options, may be a key to creating a resource-efficient medical decision-making process.

3. Research Design/Methodology: A two-stage framework for customized medical decision-making

Our approach to customized medical decision-making is based on a study of the preferences of patients for alternative procedures for preventive screening, and how stable the preferences are to changes in the importance weights of the criteria used to make the medical decision. Stability refers to how the patient's most preferred alternative may change as the criteria weights change; criteria weights may change when the patient learns more about the pros and cons of the alternatives. We are interested in the characteristics of the changes in preferences for the procedures considered. Those characteristics determine the way in which customization occurs via group-level customization or via individualized analysis.

3.1. Stability analysis of preferences – a simple example

Stability analysis captures the characteristics of a decision-maker's preferences (May et al, 2013; Sava et al, 2020; Sava et al, 2022). We illustrate the process of stability analysis with a simple example. Consider the following Analytic Network Process (ANP) model, consisting of three criteria (C_1, C_2 and C_3) and three alternatives (A_1, A_2 and A_3). The associated supermatrix, the criteria weights, and the limiting priorities for the alternatives are shown in Table 1.

Alternative A_1 is the most preferred alternative, but perturbing the criteria weights may yield a different most preferred alternative. Stability analysis consists in finding the minimum perturbations of the criteria that would shift the most preferred alternative from A_1 to another alternative, A_j. Consider, initially, perturbations of only two criteria, C_1 and C_2 (Appendix A). Perturbations are measured in terms of the proportion of the distance from a criterion's current weight to the boundaries on that weight, and so range from -1 to +1. For each perturbation, we find the limiting priorities for the alternatives, and the alternative that dominates at that point. The plot of the C_1xC_2 perturbation space shows the regions in which each of the three alternatives dominate (Figure 1).

Table 1. The supermatrix and limiting priorities

		Goal	C_1	C_2	C_3	A_1	A_2	A_3	**Criteria weights & Limiting priorities**
	Goal	0	0	0	0	0	0	0	
	C_1	0.70	0	0	0	0.10	0.25	0.25	0.1892
	C_2	0.10	0	0	0	0.80	0.50	0.50	0.6216
W =	C_3	0.20	0	0	0	0.10	0.25	0.25	0.1892
	A_1	0	0.10	0.50	0.40	0	0	0	***0.4054***
	A_2	0	0.40	0.10	0.50	0	0	0	***0.2324***
	A_3	0	0.50	0.40	0.10	0	0	0	***0.3622***

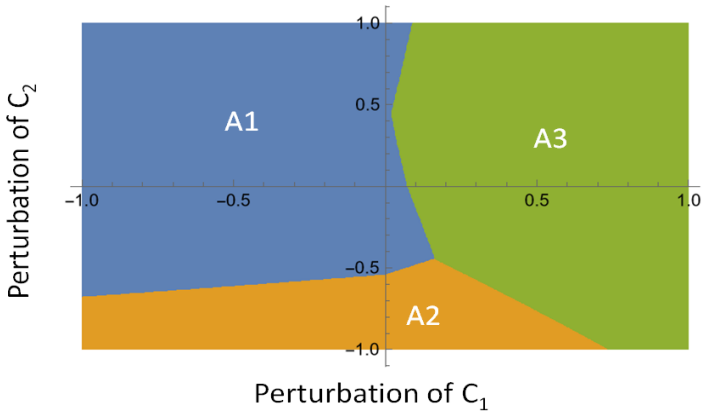

Figure 1. The C_1xC_2 perturbation space

The point (0,0) in the C_1xC_2 perturbation space corresponds to the initial, unperturbed supermatrix, where alternative A_1 dominates. From that point, we can calculate the shortest distance to the boundary of each region in which each of the other alternatives dominate. We call this the *perturbation stability*. For example, at the boundary between the A_1 and A_3 dominance regions, the limiting priorities of A_1 and A_3 are equal, and movement along a vector from (0,0) to the A_1-A_3 boundary corresponds to the following set of perturbations of the criteria weights $(-0.0684; 0.0232)$, leading to the perturbation stability distance of 0.0852.

To provide a complete picture of the impact of all criteria perturbations on the most preferred alternative, Sava et al. (2022) developed a multi-dimensional stability analysis (Appendix A and Appendix B). To implement the multi-dimensional stability analysis in our framework, we use the *perturbation stability* measure, which is defined over the criteria $(C_1, \dots, C_m)$, and which is given by the distance from the center of the perturbation space 0^m, to each of the boundaries. The calculated distance from the origin of the region of the initially most preferred alternative A_i to the *nearest* boundary is termed the *minimum switch distance*, and the alternative that dominates when moving across the boundary is termed the *minimum switch alternative*. Calculating the distances to each of the boundaries yields the *number of possible switches* from the initially most preferred alternative A_i to other alternatives.

3.2. A hybrid customization approach for medical decision-making

The resource expenditure involved in an individualized elicitation and analysis of

preferences might be avoidable if the stability analysis of a patient's preferences could be predicted, with sufficient accuracy, using non-preference-related information. In this section, we describe our approach to deciding if an individualized analysis should be performed, and to providing a predicted stability profile if a group-based analysis, instead of an individualized analysis, might be used. Using group-based predictions for at least some patients, instead of individualized analyses for all patients, may require accepting a degree of prediction error, in order to achieve a savings in resource expenditure. In addition, our model permits the decision-maker to choose the degree of acceptable error by customizing the model. In Figure 2, we provide a graphical representation of the proposed framework.

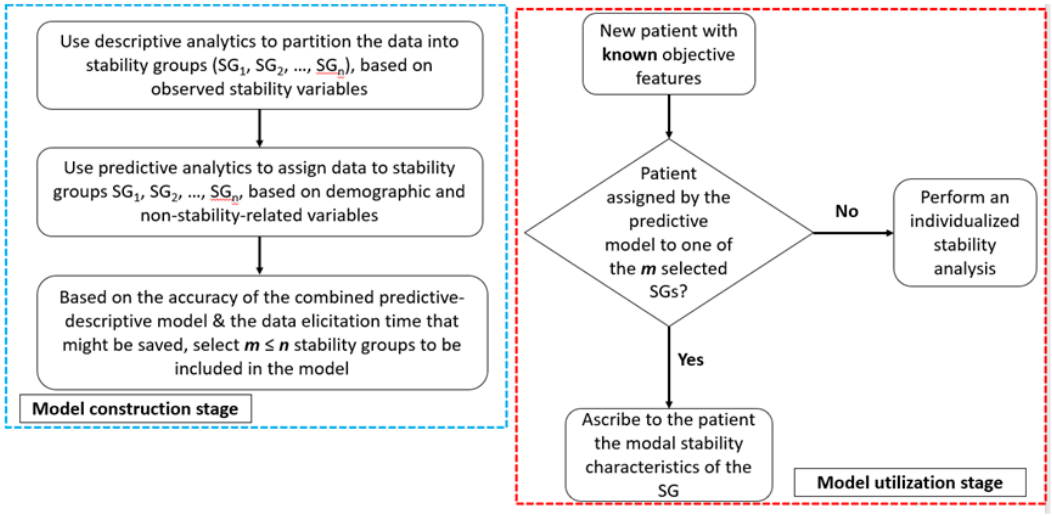

Figure 2. A two-stage hybrid customization for medical decision-making

Our framework begins by partitioning a set of patients (which we call the training set/ partitioning set), whose preferences have been individually elicited and analysed, based upon the relevant characteristics of a stability analysis of each of their preferences. We call each partition a *stability group*. Each stability group is characterized by the proportion of the partition's members that are correctly described by a stability profile derived from the members of the stability group. The number and variety of the stability groups is a function of the set of patients and of the partitioning technique used. After the partitioning has been performed, the next step is to construct a model to assign a different set of patients (which we call the prediction set), whose preferences have also been individually elicited and analysed, to the stability groups.

4. Results/Model Analysis: Two-stage hybrid customization for colorectal cancer screening

The framework described in Section 3 can be applied, with minor adjustments, to any medical decision-making problem that requires the input of patient preferences. Examples of such decisions include screening for breast cancer (US Preventive Services Task Force, 2016a), ovarian cancer (USPSTF, 2018a), and prostate cancer (USPSTF, 2018b). For each of those, multiple screening options are available, and patients can express their preferences regarding the options. To operationalize the process and to show how it can be implemented in clinical practice, we demonstrate its applicability for the selection of a most appropriate colorectal cancer screening procedure. Colorectal cancer is the third deadliest form of cancer in the U.S. (American Cancer Society, 2019), but it is

also one of the most preventable. Preventive cancer screening involves a proactive set of measures that can affect a patient's disease progression. It is a preference-based decision in which interested patients can provide their input. The U.S. Preventive Services Task Force (2008; 2016b) guidelines recommended regular colorectal cancer screening for all patients between 50 and 80 years old.

4.1 Data set description

To show the applicability of the proposed framework to group-level customization we are using a synthetic data set based on the original data collected by Dolan et al. (2002; 2013; 2014). The initial data set included objective data fields such as a patient's age, gender, and the location of the patient's primary care physician (PCP), as well as the patient's preferences with respect to ten colorectal cancer screening alternatives. We augmented the initial data set with realistic values for two other objective features: the patient's *education* level, coded as high school degree (HS), bachelor's degree (BS), graduate degree (GS) and *income*, coded as low, medium and high. All patients involved in the original research study were classified as having an average risk for colorectal cancer, so medical history, comorbidities, and other risk factors were not considered to have a direct impact on the patient's preferences. Additionally, changes in the expected medical outcomes are a function of age and gender, while location was used as a proxy factor for the level of understanding of the medical information by the patient.

Dolan's study elicited patient preferences for a set of 484 patients from PCPs in Rochester, NY, Birmingham, AL, and Indianapolis, IN. We used the 395 patients for whom the data records were complete. The background information associated with the 395 patients is given in Table 2. The descriptive statistics associated with the two additional objective features added to the original data set are presented in Table 3.

Table 2. Patients' background information

Location	**Indianapolis, IN**		**Birmingham, AL**		**Rochester, NY**		**Total**
Age/Gender	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	
50	13	4	36	8	3	4	*68*
55	13	9	28	15	4	4	*73*
60	9	5	43	16	2	2	*77*
65	9	9	31	18	2	1	*70*
70	6	3	17	11	2	6	*45*
75	5	2	20	8	-	-	*35*
80	-	1	13	4	4	5	*27*
Total	*55*	*33*	*188*	*80*	*17*	*22*	*395*

*Patients' ages have been rounded to the nearest 5 years to accommodate for the changes in the medical outcomes.

Location	**Indianapolis, IN**			**Birmingham, AL**			**Rochester, NY**		
Education/Income	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**H**
HS	13	6	3	30	13	8	11	3	
BS	14	9	16	29	65	20	3	10	
GS	1	20	6	4	54	45	0	6	
Total	*28*	*35*	*25*	*63*	*132*	*73*	*14*	*19*	

Dolan et al. (2013) used an AHP-based model to elicit the patients' preferences. A graphical representation of the model is presented in Figure 3, and an explanation of the criteria and alternatives used to elicit the patients' preferences is described in Table 4. The 10 screening options considered were based on the 2008 U.S. Preventive Services Task Force recommendation guidelines. Even though the U.S. Preventive Services Task Force

recommendations were updated in 2016, the decision-making considerations, the trade-offs, and most of the screening options have not changed since the 2008 guidelines were published.

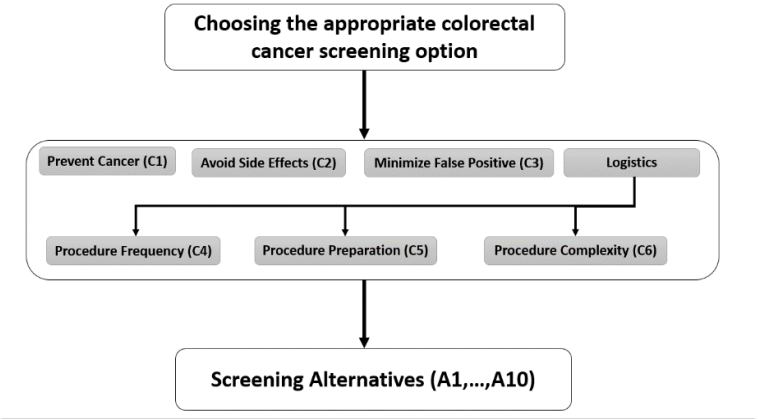

Figure 3. The AHP-Based Model for Eliciting Patients' Preferences (Dolan et al. 2013)

Based on the patients' preferences obtained using the AHP-based model, we observed that only a subset of the screening alternatives available is ever most preferred (that is, ranked first), for the set of patients analysed. Table 5 presents the frequencies of the initially most preferred screening options, cross-classified with the patients' age groups.

Table 4. Criteria and Alternatives for the AHP-Based Model

Criteria
(C1) Prevent Cancer – how accurate the screening alternative is in detecting cancer
(C2) Avoid Side Effects – the possible side effects of the screening procedure
(C3) Minimize False Positive – how often the screening procedure misidentifies a possible cancer
(C4) Procedure Frequency – how often the procedure needs to be performed (yearly base)
(C5) Procedure Preparation – what the procedure protocol involves
(C6) Procedure Complexity – how complex and invasive the procedure is
Alternatives (*level of invasiveness*)
(A1) Annual fecal occult blood test with sensitivity 20% - *non-invasive*
(A2) Annual fecal occult blood test with sensitivity 40% - *non-invasive*
(A3) Flexible sigmoidoscopy every 5 years - *invasive*
(A4) Fecal DNA test every 5 years - *non-invasive*
(A5) Annual immunochemical fecal occult blood test - *non-invasive*
(A6) Annual fecal occult blood test and flexible sigmoidoscopy every 5 years - *both*
(A7) CT colonography - *non-invasive*
(A8) Double contrast barium enema - *invasive*
(A9) Annual immunochemical fecal occult blood test and flexible sigmoidoscopy every 5 years – *both*
(A10) Colonoscopy every 10 years – *invasive*

Table 5. Initially Most Preferred Screening Alternatives

Age group	Initially most preferred screening alternatives						
	A1	**A2**	**A3**	**A4**	**A7**	**A8**	**A10**
50	1	-	6	1	-	3	57
55	2	1	11	-	-	2	57
60	-	-	15	-	-	-	62
65	-	1	13	-	-	2	54
70	-	2	6	-	1	-	36
75	-	-	7	-	12	-	16
80	4	-	7	-	-	-	16
Total (%)	***1.77%***	***1.01%***	***16.45%***	***<1%***	***3.29%***	***1.77%***	***75.44%***

4.2. Characterization for the colorectal cancer screening problem

The goal of our paper is to predict a new patient's stability of preferences, based on his/her objective characteristics, such as age, gender, location, income, and level of education. To predict the patients' preferences and their stability, we use two analytical models, one descriptive and one predictive. The descriptive model uses a set of descriptors to partition the data into stability groups. We use a clustering technique for that purpose. The accuracy of the partitioning is a function of the homogeneity of the clusters. The predictive model uses a different set of descriptors to assign new observations to the stability groups that result from the descriptive model. We use a tree model for that purpose. The accuracy of the predictive model is a function of the accuracy of the tree. The overall ability of the complete model to predict the stability characteristics of new patients depends on the accuracy of the descriptive model and the accuracy of the predictive model. For validation purposes, we randomly divided the data into a training set (300 patients) and a prediction set (95 patients).

The model obtained using the two-step clustering was further applied to the prediction set (Table 6).

Table 6. Characteristics of the Stability Groups prediction set (Two-step clustering)

Initially most preferred alternative	Minimum switch alternative								% out of total
	A1	**A2**	**A3**	**A4**	**A5**	**A7**	**A8**	**A10**	
Stability Group 1									***63.16%***
A10			**100%***						
Stability Group 2									***20.00%***
A3	5.26%				5.26%	5.26%			
A10	21.05%	21.05%		5.26%	15.79%	10.53%	**10.53%**		
Stability Group 3									***16.84%***
A3	18.75%	6.25%					12.50%	**18.75%**	
A7			6.25%					18.75%	
A8		6.25%						12.50%	

* % represents the number of patients with an initial alternative A_i and a minimum switch alternative A_j. Blue bold is used to denote cells that have correct predictions based on the training set.

The results for the training set and for the prediction set are similar, with a plurality of the patients being assigned to Stability Group 1, with perfect stability measure prediction. Smaller percentages of patients are assigned to Stability Groups 2 and 3, and stability measure homogeneity in those Stability Groups is much lower.

In order to use our framework in a clinical setting, we would need to identify (1) whether to match a patient with an already defined stability group, and, if so, which one, and (2) to identify patients who require individualized analysis. Ultimately, our goal is to use the objective features characterizing a patient to predict the relevant aspects of his/her stability analysis. In order to match a new patient to either a stability group or to determine that the new patient should receive an individualized stability analysis, we used decision tree-based techniques that are capable of supporting mixed predictors, such as C5 and CART. We used (1) gender, (2) age, (3) location, (4) income, and (5) education as the input variables. Stability group membership, as given by the two-step clustering, is the class variable. In order to be able to assess the generalizability of the trees generated by C5 and CART, the trees were induced from the training set and were tested on the prediction set. The decision tree built by C5 correctly classifies 74.74% of the patients into a correct stability group, and the CART decision tree correctly classifies 78.95% of the patients.

5. Clinical implications

To show how the proposed framework might be used in a clinical context, we evaluated its coherence by identifying *how many of the stability groups defined by the classification algorithm should be adopted*, as a function of the level of potential mismatch in the stability of preferences prediction. Figures 4 displays the resource gains and the potential misclassification errors, as a function of the number of stability groups used for group customization. We assume that the stability groups are adopted in decreasing order of predictive accuracy.

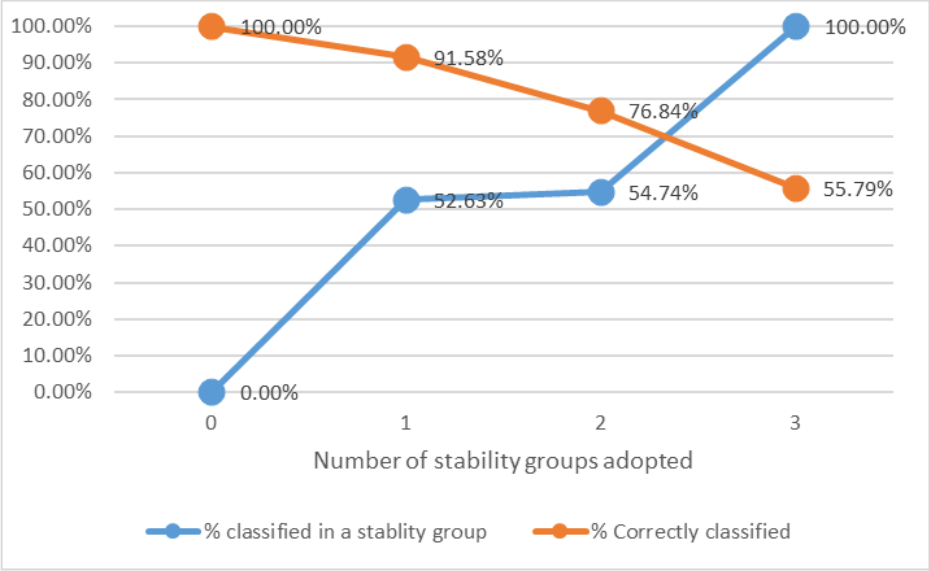

Figure 4 Group-Level Customization Trade-Off Chart, C5

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