A Data- and Expert-driven Decision Support Framework for Helping Patients Adhere to Therapy: Psychobehavioral Targets and Associated Interventions

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Abstract. Patient adherence to therapy is one of the key determinants of treatment success, while low levels of adherence potentially lead to the worsening of health outcomes and to increased health care costs. The automatic identification of psychobehavioral targets, i.e., patterns in patients' psychological characteristics and behaviors that positively or negatively affect their adherence level, should help physicians develop therapies that influence adherence and improve health outcomes. These targets can also be used to develop psychobehavioral interventions, i.e., plans of actions to modify patients' behavior and psychological stance, that maintain or improve adherence level by motivating patients to avoid negative psychobehavioral targets or to achieve positive ones. In this work, we propose a theoretical decision support framework that helps patients better adhere to therapy by automatically identifying psychobehavioral targets and selecting corresponding psychobehavioral interventions. We use data-driven techniques to discover these targets from patient data. Specifically, we apply dominance-based rough set theory to induce decision rules from data and then automatically extract targets from these rules. Once these targets are identified, we apply expert knowledge to select the most appropriate generic psychobehavioral interventions and customize them to patient characteristics. We illustrate the proposed framework using a case study of patients with atrial fibrillation who follow oral anticoagulation therapy. We describe the psychobehavioral targets identified from data and present associated psychobehavioral interventions.

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1 Introduction

One of the most significant barriers to effective medical treatment is patients' failure to follow advice and recommendations from their healthcare provider. A Cochrane review by Haynes et al [1] concluded that interventions for enhancing therapy adherence can have a far greater impact on clinical outcomes than improvement in therapy. Non-adherence comes at a significant cost – the Institute for Healthcare Informatics estimated that between $100B and $300B of avoidable health care costs have been attributed to patients' non-adherence in the US annually [2]. Rates of adherence vary according to the type of therapy. According to the World Health Organization, adherence to long-term therapies in the general population is around 50% in developed countries and lower in developing ones. Moreover, adherence to short-term therapy has been estimated as 70-80%, however complying with lifestyle changes is very low and reported to be 20-30% [3].

Interventions that involve patient education and behavior modification are commonly used with the aim of improving adherence. A systematic review of strategies to improve adherence to self-administered medications for chronic diseases in the US examined the effectiveness of interventions and concluded that case management and patient education with behavioral support improved medication adherence for more than one condition [4].

In this paper, we propose a theoretical decision support framework for the development of psychobehavioral interventions to help patients with their adherence to treatment. The framework involves two phases. The first phase is data driven and it is aimed at identifying psychobehavioral targets, defined as patterns in patient's psychological characteristics and behaviors that affect adherence. Here we apply a dominance-based rough set approach (DRSA) [5] to induce decision rules from patient data. Obtained rules capture the relationship between a patient's sociodemographic, psychological and behavioral characteristic [6] and adherence level, and from these rules we identify the psychobehavioral targets. In the second phase, we propose to use expert knowledge to select psychobehavioral interventions, i.e., systematic plans of actions that affect patients' behaviors and psychological stance, that are appropriate for the targets and to customize them for a given patient. For example, a psychobehavioral target that implies limiting smoking to at most a light level may require an intervention that involves education (customized to the patient's level of health literacy) about negative consequences of moderate and heavy smoking and goal setting exercises along with self-monitoring (operationalized as reporting of smoking behavior).

We illustrate the proposed framework in the context of patients with atrial fibrillation (AF) whose adherence to oral anticoagulation treatment we aim to improve. We present the psychobehavioral targets and explain how they were identified. We also describe possible interventions that correspond to the targets.

2 Methods

2.1 Foundations of DRSA

In this section we introduce those DRSA notions and concepts that are relevant for our framework – a detailed presentation of DRSA can be found in [5]. DRSA is a data analysis and knowledge discovery technique aimed at analyzing imperfect (e.g., inconsistent or incomplete) data. It assumes analyzed objects (e.g., patients, customers) are categorized into ordered classes, typically from worst to best, and they are described with features (with symbolic and numerical domains) whose values may also be ordered (such features are referred to as criteria). Instead of individual classes, DRSA considers their unions, e.g., a set of classes that are at least or at most as good as a given class. Such unions appear in consequences of decision rules; therefore, these rules are referred to as *at least* or *at most* decision rules.

DRSA allows decision rules to be viewed from two perspectives – classification- and intervention-oriented [7]. In the classification-oriented perspective, the premise of a rule captures selected features of an object, and the consequence predicts an outcome (a union of classes) associated with these features. The intervention-oriented perspective assumes there are some interventions that may be used to change the object's features and that these changes affect the object's classification. Then, the premise of a rule defines the target for intervention and its consequence indicates an outcome resulting from achieving the target. Both perspectives adopt a different interpretation of decision rules, however, they do not impose any special requirements on algorithms used for their induction. Thus, the same algorithm may be used to obtain both types of rules.

Formally, let us assume *r* is a rule $\phi \rightarrow \psi$ derived from a set of objects U, where ϕ is a premise (a conjunction of conditions on selected features) and ψ is a consequence (a union of decision classes) decision. A rule *r* is also characterized by its confidence (or certainty) denoted as $conf(r, U)$, which is a conditional probability $P(\psi|\phi)$ established in U.

Within the intervention-oriented perspective, ϕ indicates an intervention target and ψ is a resulting classification given as a union of classes. If ϕ is achieved by objects that currently do not match it and that do not belong to ψ, then their classification will change and become consistent with ψ. A success rate associated with achieving a target is approximated by the confidence of *r*.

An intervention target indicated by the premise of rule *r* can be evaluated using its *impact*, defined as the ratio of objects affected by achieving the target. Intuitively, impact indicates how "strong" a target is – the higher the impact, the more objects are affected by the target. Impact is established in the context of *r* and using the set U' (possibly different than U, however, both sets should be homogeneous) and formally it is defined as:

$$\delta(r) = \frac{|m(\neg\phi, U') \cap m(\neg\psi, U')|}{|U'|} \times conf(r, U), \tag{1}$$

where $m(\gamma, X)$ is a set of objects from X that satisfy the condition γ (note that in the above formula negated conditions are considered).

There are, however, certain situations where it is reasonable to limit the set of objects that achieve the target by introducing *applicability profiles* acting as additional conditions imposed on these objects. Formally, an applicability profile ϕ_i is defined analogously to ϕ as a conjunction of conditions on selected features. Then, the impact of the psychobehavioral target is redefined as:

$$\delta(r) = \frac{|[\cup_{i=1}^{v} m(\phi_i,U')] \cap m(\neg\phi,U') \cap m(\neg\psi,U')|}{|U'|} \times conf(r,U), \quad (2)$$

where v is the number of considered applicability profiles.

There are two types of intervention targets – positive and negative. Positive targets are associated with changes that improve class assignment (i.e., an object gets assigned to a better class) and they are given as premises of *at least* decision rules. On the contrary, negative targets correspond to changes that result in deteriorated class assignment (i.e., to a worse class) and they are given as premises of *at most* decision rules.

2.2 Identification of Psychobehavioral Targets

The intervention-oriented perspective in DRSA described in Section 2.1 needs to be adapted to the problem of adherence support. We can no longer assume that an intervention changes any possible characteristic of a patient (i.e., value of any feature). Patients are characterized by sociodemographic, psychological and behavioral features, and only the features from the last two groups can be modified by an intervention – for example it is possible to affect a patient's smoking habit, while it is impossible to change a patient's age. In the subsequent text, we refer to features from the last two groups as to *psychobehavioral* features and distinguish them from *sociodemographic* ones.

Given the distinction between sociodemographic and psychobehavioral features we expand the formal representation of a rule r to $\phi_{pb} \wedge \phi_{sd} \rightarrow \psi$, where ϕ_{pb} is a conjunction of conditions on psychobehavioral features, ϕ_{sd} is a conjunction of conditions on sociodemographic features, and ψ is an at least or at most union of adherence levels. Moreover, ϕ_{pb} defines a *psychobehavioral intervention target* (*psychobehavioral target* in short), and ϕ_{sd} defines a *sociodemographic context* (or a sociodemographic characteristic, e.g., age > 55 years and at least middle socioeconomic status).

For induction we use the VCDOMLEM algorithm [8] that produces a minimal set of rules, i.e., a smallest set of rules that capture all patterns in a data set. It is possible to obtain rules with an empty sociodemographic context or psychobehavioral target. Rules with an empty ϕ_{pb} are of no use (they indicate no psychobehavioral target) and are discarded. In order to minimize the number of such rules we perform preliminary feature selection. For this purpose we identify so-called *reducts* [5] – minimal subsets of features that have the same discriminatory power as the entire set of features. If there are multiple reducts, then we select the one that contains the largest number of psychobehavioral features. Finally, we expand the selected reduct with the remaining psychobehavioral features, if any. While this expansion may make the obtained set of features not a minimal one, it allows us to identify more psychobehavioral targets. At this point it is still possible to obtain rules with an empty ϕ_{pb}, however, their number is smaller than when considering the entire feature set.

Splitting the premise of a rule into ϕ_{pb} and ϕ_{sd} calls for a revised measure to evaluate the impact of the former. As previously stated, we evaluate the target in the context of a rule *r* that contains it and of the set U'. The updated definition is the following:

$$\delta(r) = \frac{|m(\phi_{sd}, U') \cap m(\neg\phi_{pb}, U') \cap m(\neg\psi, U')|}{|U'|} \times conf(r, U). \quad (3)$$

Comparing definition (3) with (2) we see that the sociodemographic context ϕ_{sd} acts as an applicability profile that limits the impact of the psychobehavioral target ϕ_{pb} to those patients who match ϕ_{sd}.

We also distinguish between positive and negative psychobehavioral targets. A positive target is identified by an at least rule and calls for a psychobehavioral intervention that will help a patient achieve this target, while a negative target is identified by an at most rule and requires an intervention that will prevent a patient from achieving the target. This leads to the following layman's interpretation of at least and at most rules, respectively:

- if the intervention associated with the positive target is successfully applied and the patient manages to achieve this target, then his/her adherence level will improve,
- if the intervention associated with the negative target is successfully applied and the patient manages to avoid the target, then his/her adherence will not deteriorate.

Here we need to observe that it is possible that an induced rule captures correlation, not causation, between a psychobehavioral target and an adherence level. This will manifest as not improving adherence after the positive target has been attained, or not maintaining adherence after the negative target has been avoided. To account for such undesired situation we plan to add a feedback loop to monitor changes in patients' adherence, identify rules with poor causality and discard those rules.

2.3 Selection of Psychobehavioral Interventions

Psychobehavioral interventions combine patient education and behavioral modification. The latter makes use of a series of actions that rely on behavior change techniques catalogued in [9]. Many of these techniques employ behavioral economics principles [10] such as: establishing commitment, offering rewards for adherence, and leveraging social influence.

Patient education is focused on providing information about behavior-health links, educating on consequences of certain behaviors, and providing instructions about proper behavior. In addition to explaining the disease manifestation and its prognosis and management, patient education needs to emphasize the key role that the patient plays in successful therapy through her/his engagement and adherence to care. Education should be customized to the type of a target that the given intervention is associated with. For a positive target, it should demonstrate how a patient's state will deteriorate if he/she fails to change the behavior (the principle of *loss aversion*). In the case of a negative target, it should show the benefits of maintaining the current good behavior.

Patient behavior modification needs to be focused on engaging in goal setting, providing feedback on goal attainment, and providing encouragement for positive behavior. Critical in behavior modification is monitoring whether a patient is adhering to treatment as well as working towards his/her set goals. Self-reporting (more generally self-monitoring) can be used for this purpose and may even increase adherence to therapy [11]. Accuracy of reporting can be increased by another behavioral economics strategy called *priming for honesty* [10] that requires a patient to sign his/her adherence report before submitting it. Adherence and engagement with therapy can be monitored by measuring changes in the patient's level of self-determination to embrace a desired behavior [12] (the more autonomous motivation, the better the engagement and outcomes), as well as changes in his/her perceived competence and self-efficacy for treatment adherence [13].

We use the Transtheoretical Model (TTM) [14] as a theoretical cadre for psychobehavioral interventions. Drawing from many psychotherapy theories, TTM provides a comprehensive understanding of behavior change and allows classifying patients according to where they are in their readiness to change. The TTM proposes sequential stages of change, from pre-contemplation (the patient has yet to recognize the need to change), contemplation (the patient considers change), preparation (the patient plans to take action toward change), action (the patient begins to take actions that induce change), and maintenance (the patient has succeeded in changing behavior and focuses on maintaining the new behaviors in his/her lifestyle). The TTM acknowledges that some patients relapse (the patient returns to the pre-change behaviors). The current stage in the TTM is established through a patient's answers to a short set of questions [15]. It should drive the customization of actions constituting a behavioral intervention, given that what will work for a patient for example, at the action stage, may not work for a patient at the pre-contemplation stage.

3 Case Study: Management of Atrial Fibrillation

In this section, we present a clinical case study where we apply our proposed framework to help atrial fibrillation (AF) patients with their adherence to oral anticoagulation therapy. We start by presenting the patient data and providing insights into the feature selection process. Then we describe the psychobehavioral targets identified from rules induced from these data. Finally, we describe interventions associated with the targets.

3.1 Analyzed Data and Selected Features

In this case study, we used 12 vignettes describing patients with AF. We prepared them based on systematic reviews concerned with the use of anticoagulation in AF management and using expert knowledge. The vignettes were vetted and revised by the hematologist on our team who ensured they represented typical situations encountered in his clinical practice. Although real data would be preferred, after consulting with the clinicians we are convinced that psychobehavioral targets discovered from vignettes are realistic. Each vignette is described by 10 features and associated with one of three outcomes of adherence level classes corresponding to poor, average, and good adherence levels. Ideally, all sociodemographic, psychological and behavioral features indicated in [6] should be collected, however, in practice they are usually not explicitly recorded and therefore we have focused on those features that could be reconstructed from information available in patient records.

Among all the features we have one behavioral feature describing tobacco smoking or alcohol intake, one psychological feature describing patient's willingness to be in charge of his/her health and seven sociodemographic features (i.e. age, socio-economic status or employment status). There is also one feature that describes history of adherence (i.e., a pattern of past behaviors) – it is not referenced in [6] and in our analysis we considered it as a sociodemographic one.

In the feature selection step (see Section 2.2 for details) we identified a subset of three features (one of the reducts) that impact the adherence level: history of adherence, tobacco smoking or alcohol intake, and willingness to be in charge. The first feature is sociodemographic and it cannot be affected by any intervention, while the second and third are psychobehavioral features and can be changed. To further validate this selection we applied the UTA (UTilities Additives) method [16] to construct a value function (or score) for adherence. The results obtained from UTA analysis confirmed our chosen subset of features.

Vignettes with descriptions limited to the selected features are given in Table 1 (in the subsequent text we will use shorter names for the features presented in this table)[1]. In this table, as indicated by the numbers in parenthesis, we show the ordering of values for features and the ordering of adherence levels (decision classes).

Values of some of the features in Table 1 aggregate several precise values, i.e., none_or_moderate for adherence_history or none_or_light for smoking_or_alcohol. This aggregation captures domain knowledge implying that from the perspective of the adherence level, lack of adherence history is equally important as having moderate history, and light smoking or alcohol intake is equally important as none.

[1] Due to the page limit, we are not able to present the full feature list of vignettes in the paper but it is available as an on-line appendix at http://www.cs.put.poznan.pl/swilk/kr4hc2017/vignettes.pdf

Table 1. Vignettes considered in the study

	Adherence_history	Smoking_or_alcohol	In_charge	Adherence_level
v1	(3) good	(2) moderate	(2) yes	(2) moderate
v2	(2) none_or_moderate	(1) none_or_light	(2) yes	(3) good
v3	(2) none_or_moderate	(1) none_or_light	(1) no	(2) moderate
v4	(1) poor	(1) none_or_light	(2) yes	(1) poor
v5	(2) none_or_moderate	(3) heavy	(1) no	(1) poor
v6	(1) poor	(2) moderate	(1) no	(1) poor
v7	(3) good	(1) none_or_light	(2) yes	(3) good
v8	(2) none_or_moderate	(1) none_or_light	(1) no	(2) moderate
v9	(2) none_or_moderate	(1) none_or_light	(1) no	(2) moderate
v10	(3) good	(2) moderate	(2) yes	(2) moderate
v11	(2) none_or_moderate	(1) none_or_light	(2) yes	(3) good
v12	(1) poor	(3) heavy	(1) no	(1) poor

3.2 Identified Psychobehavioral Targets

Given the limited size of our data set we used the leaving-one-out (LOO) scheme to induce decision rules and to evaluate targets. We iterated over 12 vignettes – in each iteration 11 vignettes formed a derivation set used to induce rules with targets, and one vignette was used to evaluate their impact. The number of induced rules was constant across iterations – each time we obtained 7 rules. Finally, the impact of specific targets was averaged over those iterations in which they were identified.

In Table 2 we present the most frequent decision rules that were induced following the LOO scheme. There are three *at least* rules (r1-r3) and four *at most* rules (r4-r7). The confidence of all these rules is equal to 1.0. Rules r4-r7 were obtained in all LOO iterations, and rules r1-r3 in all but one, where they were replaced by rules with simplified conditions. Two rules – r2 and r4 (both marked with gray background in Table 2) – contain an empty psychobehavioral target and they were discarded from further evaluation.

Table 2. Decision rules prevalent in the LOO scheme

	Sociodemographic context	Psychobehavioral target		
	Adherence_history	Smoking_or_alcohol	In_charge	Adherence_level
r1	>= none_or_moderate	<= none_or_light	>= yes	>= good
r2	>= good			>= moderate
r3	>= none_or_moderate	<= none_or_light		>= moderate
r4	<= poor			<= poor
r5		>= heavy		<= poor
r6			<= no	<= moderate
r7		>= moderate		<= moderate

Table 3 presents the average impact of psychobehavioral targets established from specific rules. For each target, we identify vignettes that are impacted by this target. The two targets with the largest impact are those included in the premises of rules r1 and r5 and they drive the selection of psychobehavioral strategies. The target indicated in r1 is a positive target. It states that making a patient be in charge of his/her health and limit drinking or smoking to light or none should improve her/his adherence level to good. This target impacts 6 vignettes from Table 3. The target indicated in r5 is a negative target. It states that increasing drinking or smoking intake to heavy can deteriorate a patient's adherence level to poor and it impacts 8 vignettes.

There are 3 vignettes that are not impacted by any psychobehavioral target – v4, v6 and v12. Vignettes v6 and v12 do not match the sociodemographic context specified in rule r1. The intervention associated with the target from r1 could still be applied to those patients; however, there are no rules that would explicitly predict success in such a case. Moreover, v4 would have been handled by r2, however, this rule was discarded, thus according to currently considered features, no psychobehavioral target can be specified for this patient.

3.3 Selected Psychobehavioral Interventions

During the analysis described above, we identified and selected two psychobehavioral targets that are used for intervention strategies. The positive target from rule *r1* calls for an intervention that aims at limiting (or stopping) drinking or smoking and making a patient be in charge of his/her health. This intervention would result in improving the adherence level to good. On the other hand, the negative target from rule *r5* calls for an intervention that keeps the smoking or drinking to at most the moderate level. It should maintain adherence at the moderate or good level.

Below we provide more detailed insights into possible interventions that are suggested by our framework for these two targets – the final selection is limited to these suggestions. For each intervention, we describe its components (see Section 2.3): patient education, and behavioral change and self-reporting. These descriptions are formulated initially on a high level and will be turned into actionable prescriptions when the selected interventions are implemented.

Table 3. Characteristics of identified psychobehavioral targets

	Rule/target				
	r1	r3	r5	r6	r7
Average impact [%]	54.5	9.1	66.7	25.0	25.0
	Impacted vignettes				
v1	✓		✓		
v2			✓	✓	✓
v3	✓		✓		
v4					
v5	✓	✓			
v6					
v7			✓	✓	✓
v8	✓		✓		
v9	✓		✓		
v10	✓		✓		
v11			✓	✓	✓
v12					

The intervention for the first target (from rule r1) focuses on limiting smoking and drinking and on improving patient's willingness to be in charge of his/her health through therapy. Patient education should focus then on links between heavy/moderate smoking or drinking and AF health outcomes, and on the consequences of not being in charge of one's health for adherence. Teaching materials should highlight such issues as increased risk of stroke resulting from not following prescribed anticoagulation therapy. They should also provide instructions that help the patient increase self-efficacy and autonomy in taking medications (e.g., by giving a choice when to take them within a prescribed regimen) and limiting alcohol or tobacco consumption. Finally, this material should also help the patient see and understand how the proper management of AF can improve his/her life.

The behavioral change component should start with identifying barriers to change (e.g., a habit of smoking after a meal). Then, it should support setting moderately challenging but specific goals (e.g., keeping the number of cigarettes to below 5 per day). To increase goal commitment, public announcement of patient's goals should be used. As part of self-reporting, a patient should be prompted to report on these goals at meaningful intervals (if the goal is daily, then daily prompt). Moreover, the feedback on goal attainment should be provided to encourage the patient when goals are met and to educate him/her on consequences if otherwise. This feedback can be enhanced by using peer pressure, for example realized as "hall of fame" leaderboards. Prompts and feedbacks should be relatively frequent to provide an accurate insight into patient's current behavior.

The intervention for the second target (from rule r5) focuses on keeping the patient on the right track and on maintaining his/her drinking or smoking at a reasonable (i.e., lower than heavy) level throughout his/her therapy. The teaching component can be simplified to demonstrate positive consequences of the current good behavior so it is further reinforced. Behavior modification and self-reporting should also include setting goals and prompting for reporting on their attainment. However, the frequency of prompts should be lower than those associated with r1 so that the patient, who meets these goals does not get irritated by too frequent prompts (e.g., an occasional light smoker required to report on smoking habits daily).

Finally, both interventions should be expanded with two types of prompts: real-time and daily ones. The former should be triggered when it is time to take medications and the latter should be triggered to collect a daily "check in" on therapy adherence, symptoms and events that might contribute to increased risk for bleeding.

4 Related Work

The complexity of adherence comes from an interplay of many factors related to the patient, therapy, disease, social and economic status, and healthcare system [3]. Much research has focused on detecting medication adherence and non-adherence using machine learning, see for example [17]. However, less attention has been paid to discovering psychobehavioral targets strongly correlated with adherence or non-adherence. Son et al. [18] applied support vector machines to analyze self-reported questionnaire data about medication adherence in heart failure patients. They found that gender, education, monthly income, daily frequency of medication, medication knowledge, and Mini-Mental Status Examination were important predictors of adherence. Nordmann et al. [19] identified non-compliant glaucoma patients using a Bayesian network that operated on an eye-drop satisfaction questionnaire. They found that age, self-declared compliance, and patient satisfaction with the patient-physician relationship were directly associated with adherence.

When psychobehavioral targets are identified, interventions that focus on targets can be deployed with the aim to improve or maintain adherence. Interventions that have been used in healthcare rely on behavioral economic principles (see Section 2.2) [10]. For example, social influence using a buddy system was successfully used for smoking cessation [20]. The same study also employed peer pressure in the form of feedback on the patient's performance and the mean performance of her/his peers, and publishing leader boards. The principle of voluntary commitment by investing a sum of money that would be returned to patients when they have met their goal was used in a smoking cessation program and was proven to be effective [10]. Moreover, weekly lotteries were used to increase the motivation for weight loss and to encourage stroke victims to take their warfarin medication [10].

Adherence can also be increased by reminder systems [21]. These systems can be combined with active choice principles by explaining to patients what they would lose by not receiving reminders – such an approach was effective for promoting vaccinations against the flu [22]. Moreover, efficacy of reminder systems can be optimized by combining them with alternative intervention strategies. For example, Farris et al. [23] used reinforcement learning to automatically adapt and tailor SMS communication to hypertensive patients over time and as patients' statuses and circumstances changed. Another useful tool for increasing adherence and measuring it is self-reporting. For example, the successful promotion of physical activity behavior was reported by [24] using techniques such as mobile journaling.

5 Conclusions

In this paper, we present a framework for helping a patient's adherence to therapy by identifying psychobehavioral targets that drive the identification of interventions. We describe how a DRSA is applied to automatically derive such targets from patient data and to evaluate their impact. These targets drive the selection of psychobehavioral interventions aimed at maintaining or improving adherence. We illustrate our framework with an AF management case study, and show how using this framework allows us to derive psychobehavioral targets and associate these targets with psychobehavioral interventions.

The presented case study shows that DRSA is effective at both reducing a patient's features to a minimal set that sufficiently discriminates between adherence classes, and at providing actionable psychobehavioral targets for interventions in the context of AF. Our research helps define the connection between the targets and psychobehavioral interventions. Moreover, the use of DRSA in combination with psychobehavioral interventions is applicable to patient management for other diseases as the presented approach does not make disease-specific assumptions.

We are currently working on integrating the proposed decision support framework with the architecture of the *motivational patient assistant* (MPA) system. The MPA system is meant to enhance the functionality of the MobiGuide system [25] with support for therapy adherence. We are also preparing a version of the MPA specialized for AF (AF-MPA) and we plan to evaluate it in a pilot study involving physicians (cardiologists and hematologists) and patients with AF. The patient evaluators will be asked to assess the AF-MPA on whether the system helps them feel more autonomous and competent in managing AF, whether the proposed interventions increase their quality of life, and whether the interventions help patients adhere to therapy. The physician evaluators will assess whether the AF-MPA helps their patients along the same dimensions, but also whether the interventions are medically sound, given their expertise with AF and the patient population. Such an evaluation will allow us to validate and improve the proposed interventions and help us achieve our ultimate goal of providing a comprehensive decision support system with "end-to-end" support from the primary care physician's office to the patient's home [26].

In the longer term we plan to use the proposed framework for other diseases, including hypertension and chronic kidney disease, to demonstrate its ability to identify interventions beyond those for AF.

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