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ORIGINAL ARTICLE

Modeling machine learning requirements from three perspectives: a case report from the healthcare domain

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Abstract
Implementing machine learning in an enterprise involves tackling a wide range of complexities with respect to requirements elicitation, design, development, and deployment of such solutions. Despite the necessity and relevance of requirements engineering approaches to the process, not much research has been done in this area. This paper employs a case study method to evaluate the expressiveness and usefulness of GR4ML, a conceptual modeling framework for requirements elicitation, design, and development of machine learning solutions. Our results confirm that the framework includes an adequate set of concepts for expressing machine learning requirements and solution design. The case study also demonstrates that the framework can be useful in machine learning projects by revealing new requirements that would have been missed without using the framework, as well as, by facilitating communication among project team members of different roles and backgrounds. Feedback from study participants and areas of improvement to the framework are also discussed.

Keywords Conceptual modeling · Requirements engineering · Machine learning · Data analytics · Health care

1 Introduction

Advanced analytics, that is, the use of sophisticated techniques such as machine learning algorithms for generating insights that traditional reporting and business intelligence approaches are unlikely to generate [1], is rapidly becoming an integral part of many types of software systems, services, and products [2].

The development of machine learning-based software and services is a complex process. This process includes tackling challenges such as identifying business needs and use cases for machine learning [3], converting those needs into machine learning tasks and problems [4], specifying data requirements and transformation needs, selecting algorithms and assessing trade-offs [5], and ensuring continuous alignment of identified applications with business strategies [6], among others.

A key contributor to these complexities is a conceptual gap between stakeholders on the one hand and data scientists (i.e., those who develop, apply, and/or engineer machine learning techniques) on the other. While the business side lacks a clear understanding of what machine learning can and cannot do [7], the technical side lacks knowledge of what problems are worth solving, given available data assets and business priorities [8]. This problem gets even more complex as the requirements evolve and change on the business side, while data understanding efforts are in progress from the technical side. Effective use of machine learning in enterprise requires special methods, tools, and processes [9].

Conceptual modeling, as a cornerstone of requirements engineering, can offer considerable value in effective design and implementation of machine learning solutions [10–12]. Recent work in this area has led to the development of the GR4ML modeling framework (hereafter the framework) to support requirements elicitation, design, and development of machine learning solutions for a variety of business domains

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[13]. In [14], a preliminary validation of the framework was presented by demonstrating it on three use cases. Potential benefits of the framework were illustrated in [15]. In [16], methodological steps for using the framework were provided. In [17], the framework was extended for representing generic and well-proven machine learning designs for commonly known and recurring business problems.

The main objective of the current study is to employ an empirical research method to evaluate the expressiveness and usefulness of the previously developed framework for requirements elicitation and design of machine learning solutions. In particular, the key questions explored in this study are:

- **(RQ-1)** Are the modeling concepts of the framework adequate for supporting machine learning requirements elicitation?
- **(RQ-2)** What are some of the values that the framework would offer in advanced analytics projects? And
- **(RQ-3)** What are some aspects of the framework that can be improved toward better serving its purpose?

This paper is organized as follows. We provide a brief overview of the framework in Sect 2 . Section 3 presents the research method and study design. Section 4 provides details on the steps that were taken to apply the framework to the case study domain. Section 5 presents the findings and discusses threats to their validity. Section 6 summarizes related work and highlights the contributions of this work. The paper ends in Sect. 7 with some concluding remarks and directions for future research.

2 An overview of the conceptual modeling framework

The framework consists of three complementary modeling views, which together serve to mediate the viewpoints of business people, data scientists, and data engineers. Figure 1 illustrates a simplified example of the three modeling views for the banking domain. At the top, the *Business View* provides a conceptualization of analytical requirements. It shows how Business Goals are refined into Decision Goals and Question Goals, and how such Questions can be answered by (machine-learning-generated) Insight elements. In the middle, the *Analytics Design View* represents the design of machine learning solutions for addressing the requirements expressed in the Business View. It models a solution in terms of Algorithms, Softgoals (non-functional requirements), Influences, and performance Indicators. At the bottom, The *Data Preparation View* conceptualizes the design of data preparation tasks in terms of data tables, operations, and flows.

These views are linked together to generate a holistic conceptualization of how enterprise strategies are connected to machine learning algorithms and to data preparation activities. The framework is supplemented with a set of design catalogues and patterns that codify and represent an organized body of machine learning design knowledge. Details on metamodels, instantiations, methods, patterns, and catalogues can be found in [13–17].

A new component that was added to the framework, prior to the empirical work described in this paper, is a set of user-story templates to facilitate elicitation of elements in the Business View. Figure 2 shows two templates along with examples to support elicitation of Decision Goals and Question Goals. These templates represent decision activities from the perspective of an actor (Fig. 2-A) and express their needs-to-know for making those decisions (Fig. 2-B). These templates are used later in Sect. 4 .

3 Research method

A variety of research approaches exists for evaluating and comparing conceptual modeling methods, each with pros and cons [18]. To achieve our study objectives, we employed the case study research method. The case study method is known to be appropriate for testing theories and artifacts in complex settings where there is little control over the variables [19]. The method enables collecting data and evidence about expressiveness and usefulness of the framework and hence helps to answer the research questions. These require access to rich information sources that come from multiple roles in real-world machine learning projects. The validation nature of study questions in this study also makes the case study an appropriate research approach for this work.

3.1 Units of analysis—definition of a case

The unit of analysis in this study is defined as a project conducted by a project team that ideally meets a particular set of criteria. First, the team should have previously been involved in or executed at least one analytics development project that includes some use of machine learning algorithms and techniques. This ensures the relevancy of the framework objectives to the participants of the study. Second, the outcome of the project should be currently in the form of a software product or market offering as opposed to a work-in-progress, research and development or proof of concept type of work. These criteria ensure the richness and availability of data for validating the framework and finding evidence for its usefulness. Third, the project team needs to have some basic understanding of business modeling methods and techniques. This can range from

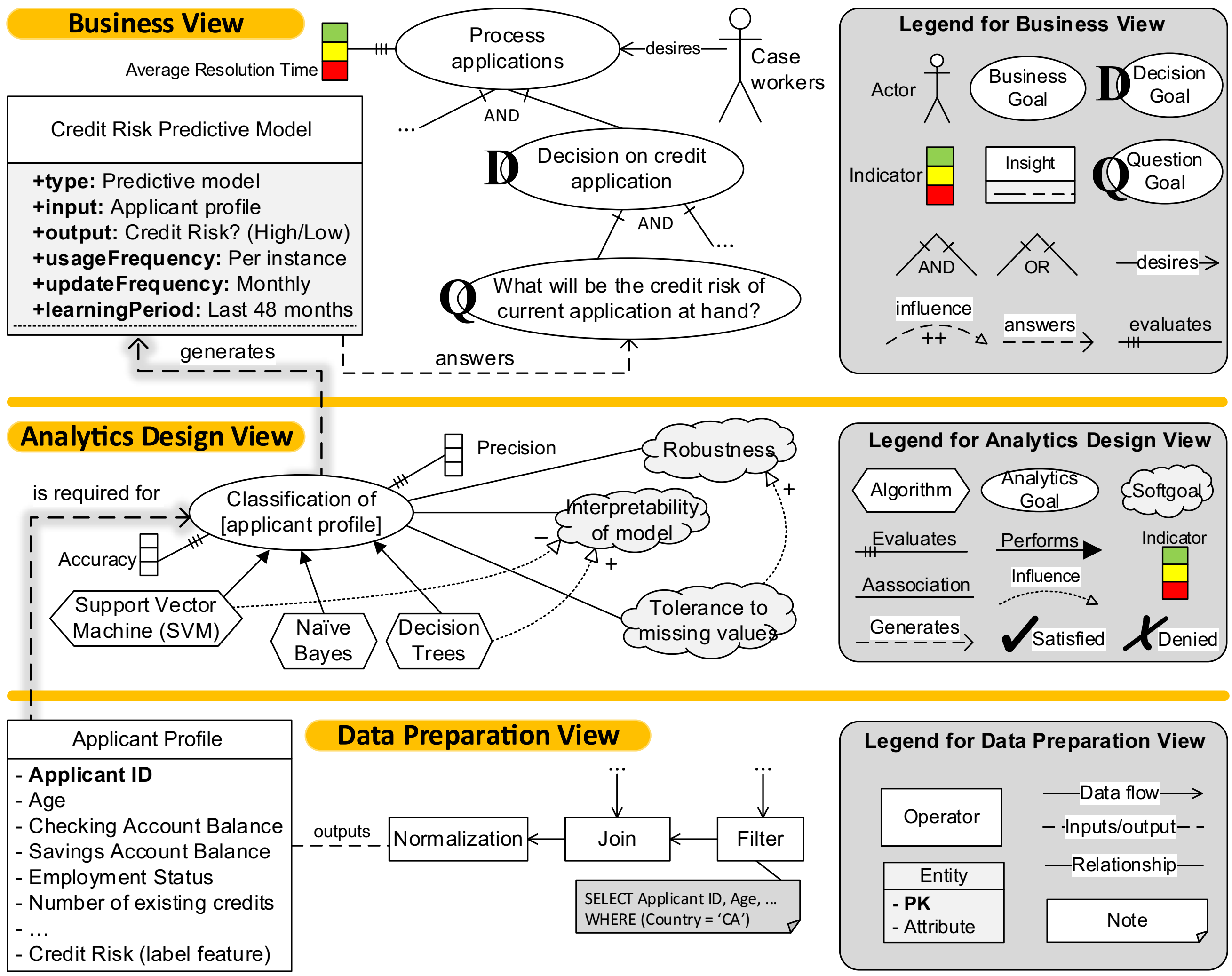

Fig. 1 A simplified illustration of the three modeling views

Fig. 2 User-story templates to support elicitation of Decision Goals (**A**) and Question Goals (**B**). Examples are for grocery retailer domain

A As a <WHO>, I need to make the <DECISION>, so that I can achieve <GOAL>.

Example. As a <STORE MANAGER>, I need to make the <DECISION ON # of CASHIERS>, so that I can <REDUCE THE WAIT AT CHECK-OUT LINES>.

B As a <WHO>, I need to know <QUESTION>, so that I can make the <DECISION>, in order to achieve <GOAL>.

Example. As a <STORE MANAGER>, I need to know <WHAT IS THE TOTAL NUMBER OF CUSTOMERS IN THE STORE?>, so that I can make the <DECISION ON # of CASHIERS>, in order to achieve <REDUCE THE WAIT AT CHECK-OUT LINES>.

high-level approaches such as business model canvas or strategy maps to more expressive and formal enterprise modeling approaches. Prior exposure to goal modeling methods was not a requirement here. These criteria ensure availability of some participants who are able to contribute to and confirm the modeling artifacts that will be created during modeling activities. Fourth, the project team requires members that represent the following roles:

- A role that involves a robust understanding of processes and operations of the business domain for which the analytics solution or product is targeted
- A role that involves extensive understanding of machine learning algorithms, including what they can do and how they can be compared
- A role that involves a keen understanding of data assets available to the team, as well as the structure, quality, and schema of available datasets

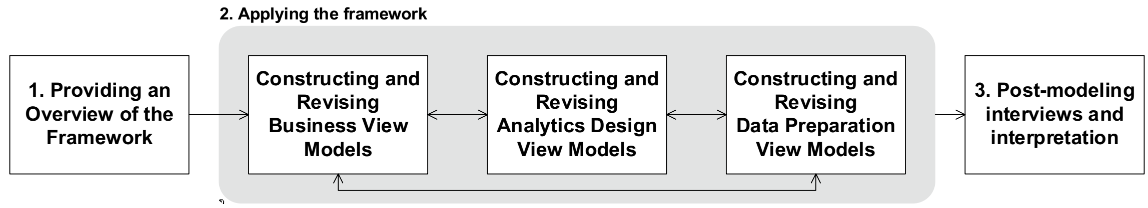

Fig. 3 Overview of Study Steps (This figure merely represents the study steps in this paper, from a research activities perspective. It should not be considered as methodological steps for using the framework.)

These criteria ensure that the project team has the required project-specific information for creating and connecting the three kinds of modeling views described in the framework.

3.2 Recruitment approach

The researchers (first two authors) contacted potential participants through their professional networks to seek out project teams that would meet the case definition requirements. A number of diverse candidate study sites were considered in the attempt to obtain generalizable and transferable research results. The recruitment activity included a short, introductory session with the prospective teams on research objectives (at a very high-level) and general questions to ensure that the candidate team would meet the definition and criteria of the unit of analysis and were willing to participate.

Subsequent to the recruiting efforts, an analytics team from a start-up company in the healthcare domain was selected. The team was responsible for developing an advanced analytics solution to enable primary care physicians and clinics (referred to as customers by participants) to enhance the effectiveness and efficiency of their clinical processes. The team consisted of eight employees with a diverse range of educational backgrounds from medicine, health informatics, health sciences, to engineering and business. Their professional backgrounds included medical doctors, clinical researchers, data scientists, database developers, and information system professionals. The researchers were blinded to any details on the company's analytics products, data assets, machine learning approaches, and solution features.[1] The researchers did not have any knowledge or background other than common-sense information about the medical domain and clinical operations.

3.3 Case study procedure

The case study was conducted in three steps (see Fig. 3).

In the first step of the study, the researchers provided the project team an overview of the framework and its components. The focus was to explain what the high-level objectives of the framework were, how the models in the three views are built and how they link to each other.

In the second step, instances of models in the three modeling views along with their connections were built in collaboration with participants. For each modeling view, a set of prompting questions were developed and used during modeling sessions to facilitate the flow and gathering of relevant information. "Appendix A" provides a list of prompting questions used in this study. All modeling sessions were held at the project team's natural setting and office environment. During the sessions, a diagramming tool was used by the modelers to write notes and create instances of elements while the participants discussed and provided information. The screen was projected in the meeting room and participants could see what was being noted/modeled during the discussion. After each session, the modelers worked on collected information to compile the notes and create/extend instances of the models in the three views. At the beginning of each session, models from the previous session were presented to and reviewed iteratively with input from the participants. Some navigation and analysis of models were demonstrated to motivate the participants to offer useful content and suggest modifications if needed. At the end, the content of the models was discussed and confirmed by the participants.

In the third step of the study, an open-ended interview was conducted with the participants to elicit their feedback about and experience of working with the framework. The focus of this step was the interpretation criteria explained in the next section. "Appendix B" provides the list of questions that were used in this step.

3.4 Interpretation criteria on expected outcomes

This section elaborates on the criteria and reasoning logic that were used to interpret the findings from the case study with respect to the three research questions. Regarding adequacy and expressiveness of the framework (RQ-1), we aimed to collect evidences that the framework could express

[1] See the section on threats to validity for further details.

or arrive at a characterization of the existing machine learning solution which was developed by the project team (prior to this study) but was deliberately not disclosed to the first two authors (here in the role of modelers). In particular, the researchers wanted to see if, by creating models in the three views, the modelers could uncover who the users of the analytics product were, what their analytical needs were and why their needs were critical, what the product offered toward satisfying such needs, what types of analytics and machine learning algorithms were used in the product, what qualities and trade-offs were considered in choosing those algorithms, what datasets were used and how they were transformed and prepared in the product.

Regarding usefulness of the framework (RQ-2), we aimed to collect instances of findings/conclusions that the project team were not able to arrive at prior to the modeling activities. In particular, we wanted to see if, as a result of modeling, new machine learning requirements could be revealed and considered as new features within the current analytics product. We also aimed to collect examples of situations where the modeling activity could trigger the participants (with different roles on the team) to communicate their ideas, discuss their understanding, and arrive at an agreement about the product.

Regarding drawbacks and shortcoming of the framework (RQ-3), we aimed to collect evidence about what makes the applicability of the framework challenging, why it is challenging and what is necessary or desirable but currently missing from the framework.

4 Applying the framework

The first two authors started out by creating the Business View models (in the role of modelers) in collaboration with participants (the third author and product architect, and other associates of the start-up organization). The first step was to identify the stakeholders of the product and their goals. Toward that, a series of prompting questions, such as “What are the key business strategies in your domain of interest?” and “Who is responsible for achieving those goals?”, were raised by the modelers while listening and drawing modeling elements at the same time (see “Appendix A” for a full list). Next, performance indicators were elicited by asking “How would these (actors/customers) measure how well you are achieving those goals?” type of prompting questions.

As a result of this, eight actors along with their goals were elicited, see Fig. 4. During the sessions, the modelers tried to position goals relative to each other so that after the sessions they could link the goals and create the hierarchy and decomposition.

After revealing Actors and their goal hierarchy, the next step was to elicit Decision Goals and Questions Goals. Toward this, a set of user-story templates (shown in Fig. 2) were presented to the participants at the beginning of this step.

After seeing the templates and examples, participants were asked to work independently and write decision and question instances on white cards that they were given. During the session, instances of goal hierarchies for each Actor were projected onto the wall so that participants could refer to the goals while filling in the templates.

Participants were then asked to present their content to the group and to suggest where in the goal hierarchy the decisions and questions belonged. This was followed by a series of conversations about each Actor and what decisions and questions matter to them. The modelers listened and navigated through the goal graph so that participants could place Decision and Question Goals (initially in the form of text) near the relevant areas.

The participants, having different areas of expertise and working independently, came up with content that had more details around their own area of expertise; nevertheless, there were some overlaps. In several cases, we observed that while a participant was presenting his/her decision and question instances, others would comment and discuss the necessity of such items for the corresponding actor. There were cases where some questions and decisions were moved from one actor to another. While the modelers were typing and placing the questions and decisions into the diagram, participants were providing comments such as “this is what our solution is currently offering,” and “this is a feature that would be valuable to the customer.” Figure 5 shows partial models, developed up to this step, for the **Physician** and **Patient with Chronic Disease** Actors.

The next step was to model Insight elements. These elements serve to translate business questions into data mining or machine learning problems. An Insight element represents the outcome of a machine learning task. It symbolizes a generalization that is learned and extracted from the data. Insights are modeled in terms of Type, Input, Output, Usage Frequency, Update Frequency, and Learning Period. Insights can have different Types such as a trained machine learning model (e.g., a predictive model, logical rules) or analysis results (e.g., a diagram). The Input of an Insight specifies what data would be used by the analytics algorithms for creating (i.e., training) the Insight and for querying it at runtime. The Output of an Insight shows what an Insight element would generate at runtime (see examples in Figs. 1 and 6).

To elicit Insight elements, participants were asked what kinds of patterns or findings would be needed to answer each question in the model. A key activity for modeling Insights was to define the Input and Output attributes of these elements. The Insight elements were then connected to the Question Goals via the Answers links. By the end of this

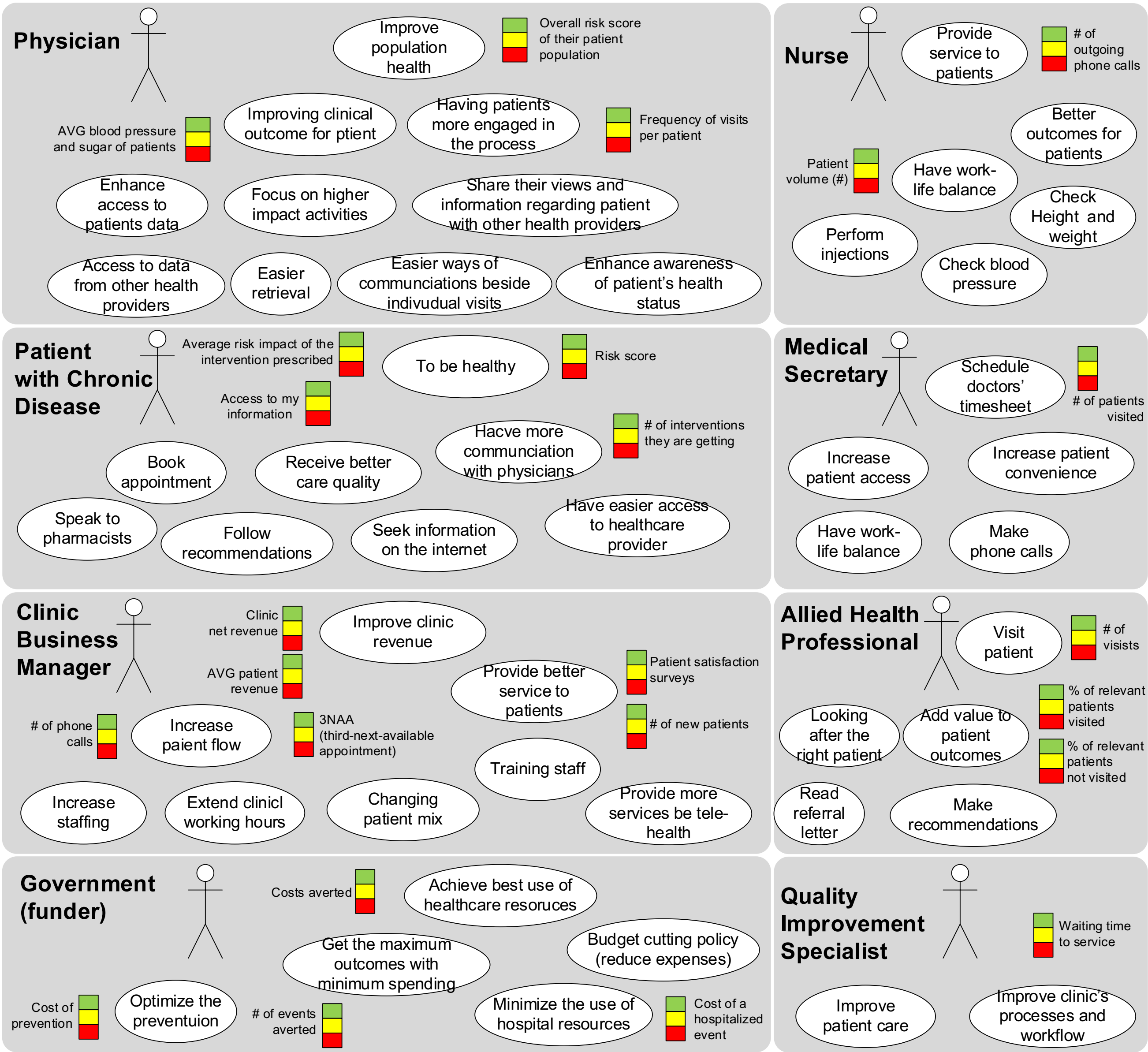

Fig. 4 Actors and their Goals elicited in the first modeling session. See Fig. 1 for legend

activity, instances of Business View models for the identified actors were created (see Figs. 6 and 7).

While specifying Insight elements, we encountered situations where by discussing the Input attributes, participants realized that their existing data assets did not (yet) include the data for generating the Insight element at hand. We also observed scenarios where after seeing the Output attributes, participants revised the corresponding Question Goal toward a more precise title. These in some cases resulted in decomposing a Question Goal that was initially too broad into further refined Question Goals.

We observed that modeling Insight elements (as the last step of Business View modeling) naturally prompted participants to provide information that was necessary for starting the Analytics Design View and Data Preparation View (see Fig. 8). In particular, we observed that:

- By specifying the Type for Insight elements, the modelers identified the Analytics Goals that would need to be performed on the dataset. This revealed the types of machine learning techniques (e.g., classification, logical rules) that are part of the existing solution. The green-shaded areas in Fig. 8 show how Insight elements (Type attributes) were used to initiate building Analytics Design Views.

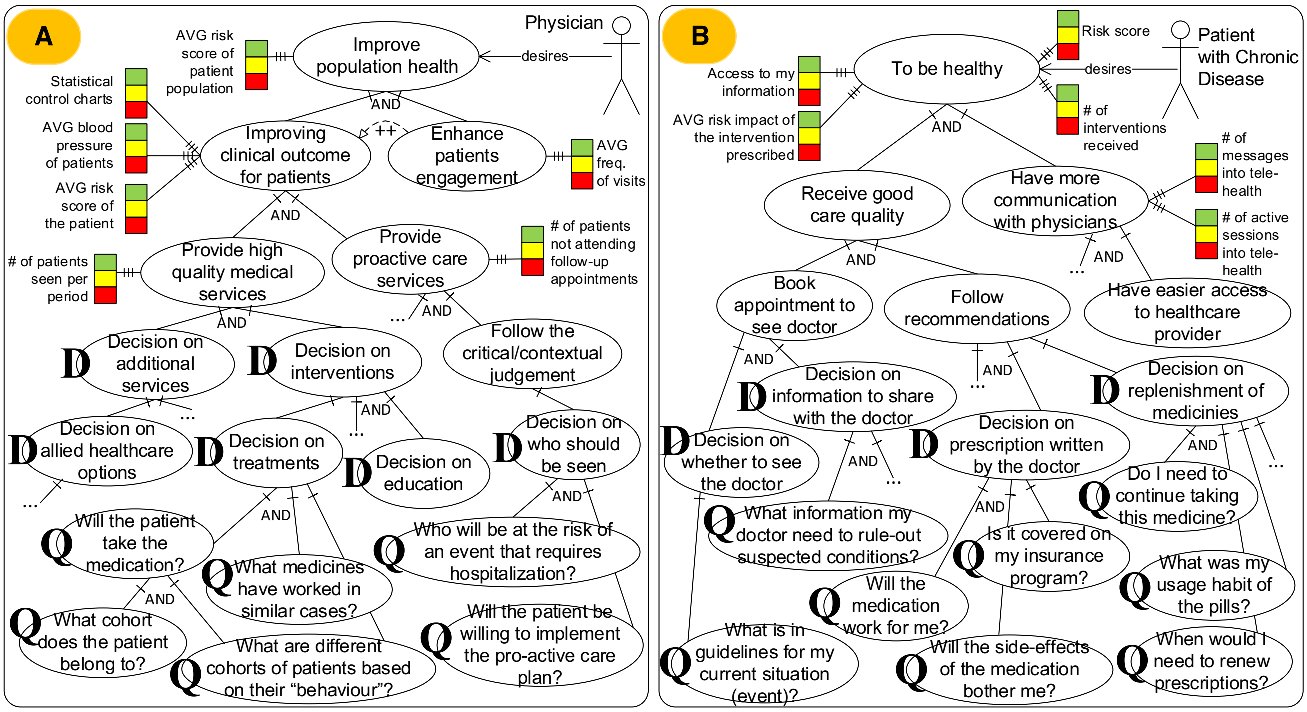

Fig. 5 Partial Business View models showing elicitation of Decision Goals and Question Goals for Physician (**A**) and Patient with Chronic Disease (**B**). See Fig. 1 for legend

- While discussing the Input and Output elements of Insights, participants started to specify what data attributes (from their existing data assets) would be required for generating the Insights and answering the questions at hand. During the session, these attributes were placed next to each Question Goal and Insight elements. The yellow-shaded areas in Fig. 8 show how Insight elements (Input and Output attributes) were used to initiate building the Data Preparation Views.

Having obtained information by the end of Business View modeling, the next step in applying the framework was to create the Analytics Design View and Data Preparation View models.

Modeling the Analytics Design View started by specifying the Analytics Goals that, if achieved, would generate the desired Insight element (green-shaded areas in Fig. 8). These goals were connected to the corresponding Insight element via the Generates links (see Fig. 9). For each Analytics Goal, a set of alternative Algorithms that can satisfy the goal were specified and connected to them via the Means-End links. Here, the modelers used the existing Algorithm Catalogues that are part of the framework [14]. Participants, some of whom had prior experience with machine learning, were shown excerpts of the models as extracted from the catalogues. Participants perceived the catalogues as an ontology that matches Algorithms to Analytics Goals. The catalogues were also used in this step to model Metrics and relevant non-functional requirements (NFRs) for the Analytics Goals at hand. The Influence links from Algorithms toward NFRs were also extracted from the catalogue. Figure 9 (middle part) shows parts of the Analytics Design View developed in this step along with their links to the Business View (top part) and Data Preparation View (bottom part).

We observed that Influence links from Algorithms toward Softgoals triggered discussion by the data scientists on why certain Algorithms were not being experimented with during development of the product. Also, there were examples where new algorithms were proposed by the modelers to be experimented with as part of the product. The content of the catalogues was seen to be very useful by the participants and applicable to their future projects.

Modeling the Data Preparation View started by specifying the prepared datasets on which the algorithm(s) would be applied and executed (yellow-shaded areas in Fig. 8 and bottom part in Fig. 9). The prepared data tables represent what the output of the data transformation pipeline should be. The next step was to understand and model the input (raw) data to the solution. The focus of this step was to analyze the data schema and attributes as well as to specify portions of data tables that are needed for the data analytics solution. In this step, the modelers reviewed Entity Relationship Diagram (ERD) documents and data dictionaries provided by the participants. Finally, the last step of creating the

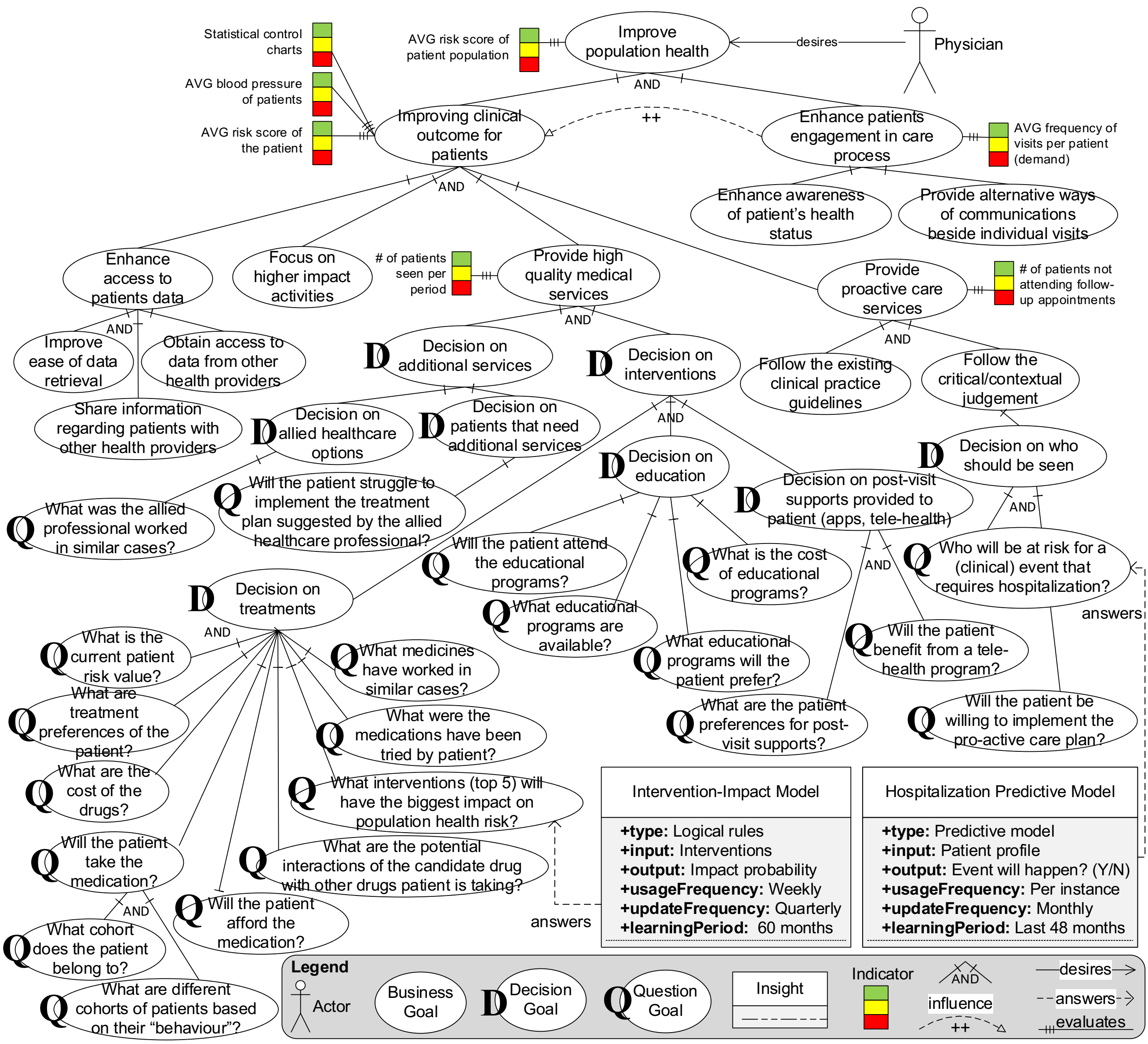

Fig. 6 Business View Model for Physician

Data Preparation View was to design how the input datasets needed to be transformed to construct and arrive at the prepared datasets. Participants who had a good understanding of existing data assets provided details on data cleansing, filtering, and noise removal logics. Figure 10 shows the Data Preparation View model developed in this step.

While creating this model, some of the participants considered the details in the model to be very close to the actual details which were proprietary and did not wish to go into further details. Also, we observed cases where the model triggered discussions on certain filtering rationales to avoid bias in the analysis results. At the end, the modelers were able to uncover the data transformation steps used in the product.

5 Findings

Having conducted the case study, we obtained a number of important findings, some of which were not evident in our previous studies. In this section, we first summarize the findings with respect to research questions and then discuss threats to validity of the findings.

5.1 RQ-1: Expressiveness

The case study provides evidence that the framework includes an adequate set of concepts for expressing machine learning requirements and design for the case study. By constructing models in the three modeling views and linking

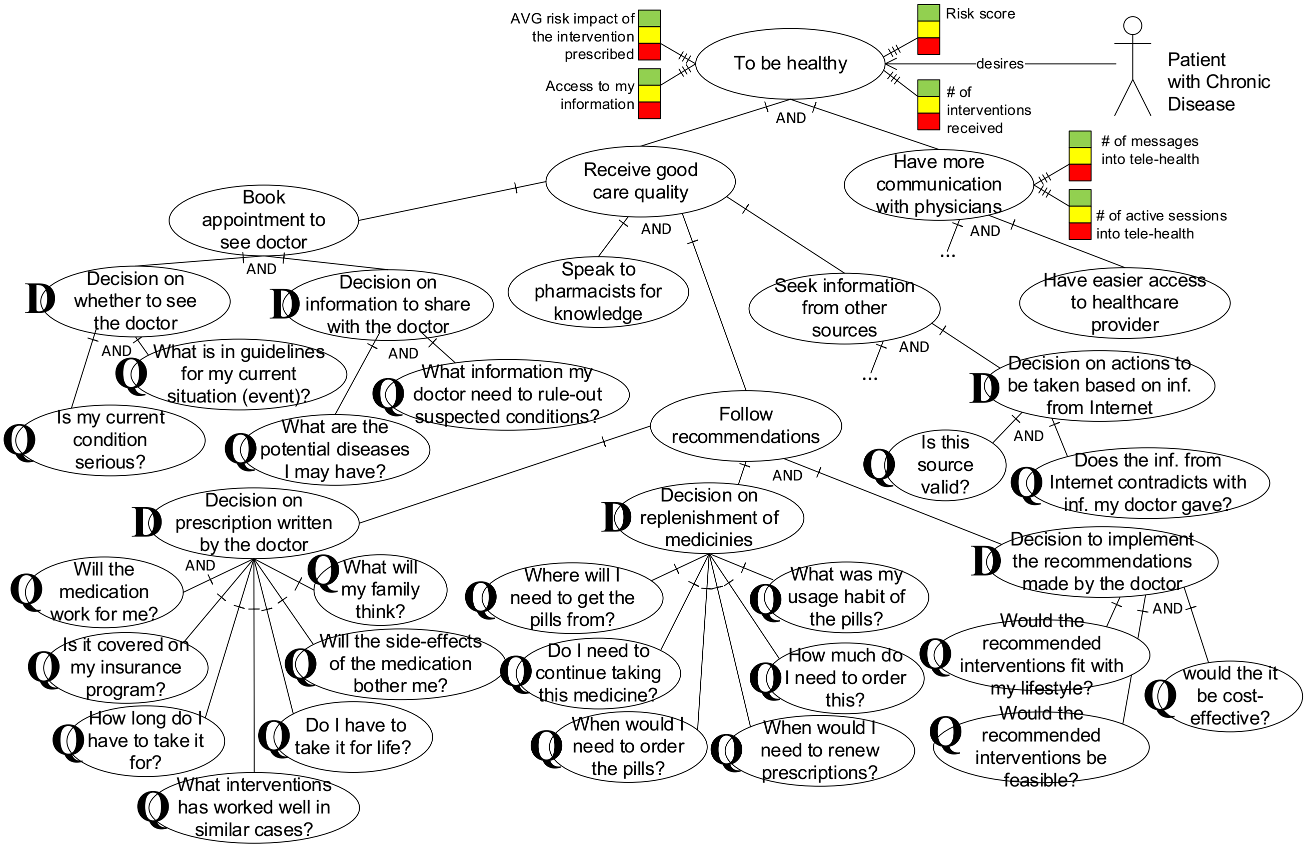

Fig. 7 Business View Model for Patient with Chronic Disease. See Fig. 6 for legend

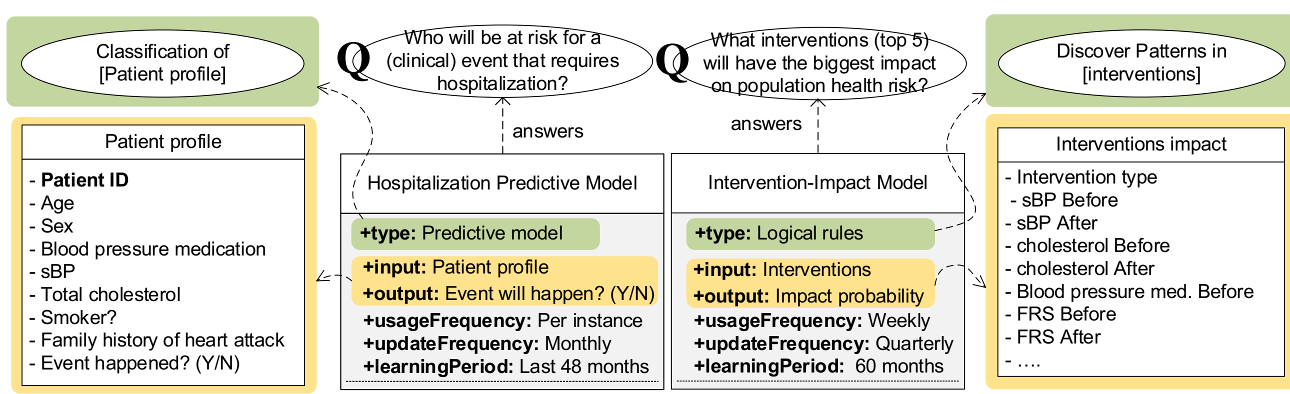

Fig. 8 Using Insight elements as a starting point to build Analytics Design View (green-shaded areas) and Data Preparation View (yellow-shaded areas) (In the rest of this paper, we use this color-coding consistently to reflect the centrality of the Insight elements as the link between the three views.)

them, the modelers (first two authors) were able to reveal the actual product scope, users, machine learning features, functionalities, data assets, and transformation steps, all being unknown to them at the beginning of the modeling activities.

By creating the Business View models, key stakeholders in the domain were found to be **Patient with Chronic Disease**, **Physician**, **Government (funder)**, **Medical Secretary**, **Nurse**, and **Clinic Business Manager**. By modeling their goals and decomposing the goals into decisions and questions, the analytical needs of stakeholders were revealed. As shown in Fig. 6, in order to **Provide proactive care services**, a **Physician** needs to make the **Decision on who should be seen**. Toward that end, the **Physician** needs to know **Who will be at risk for a (clinical) event that**

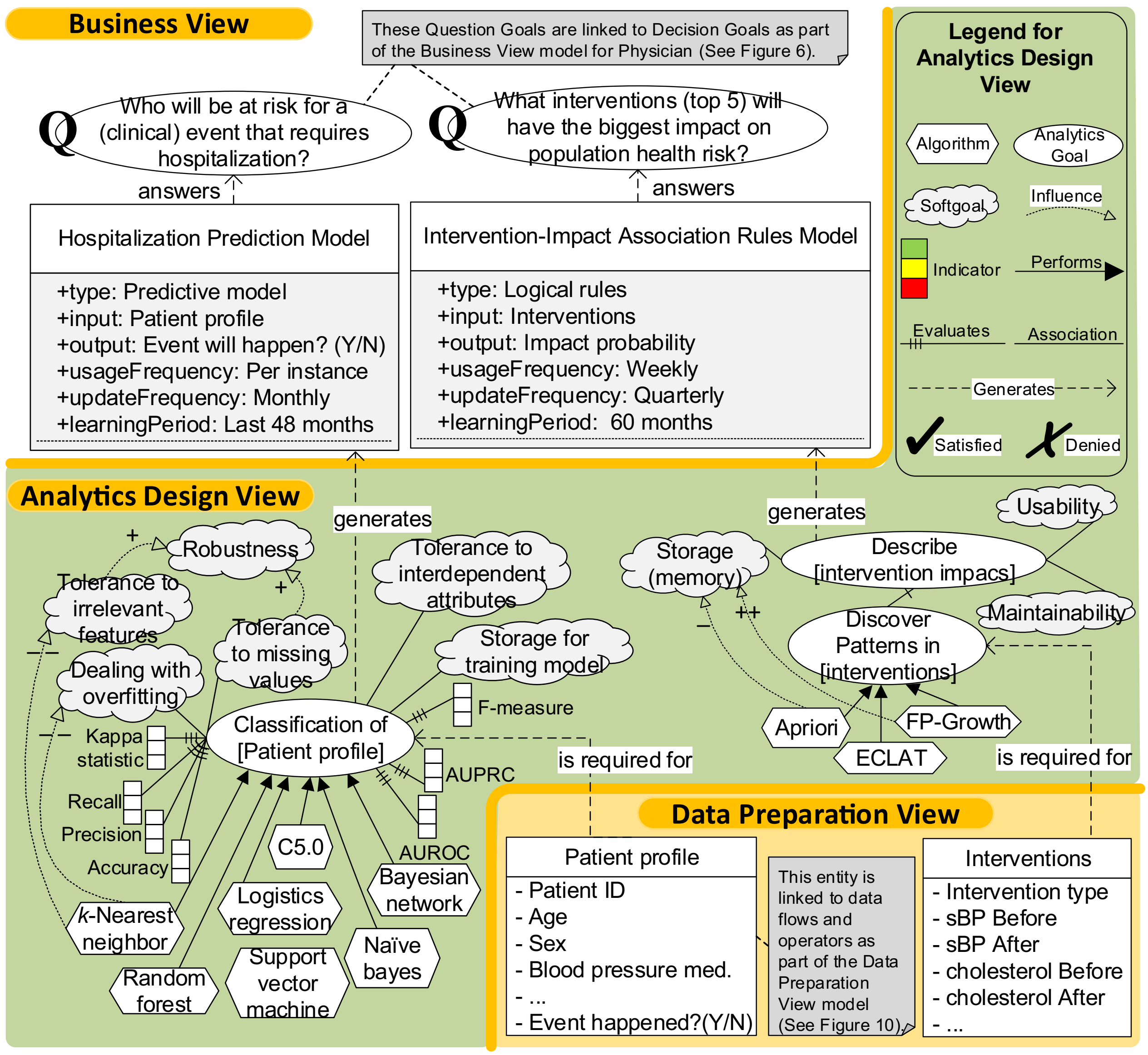

Fig. 9 Analytics Design View models (green-shaded area) linked to the Business View and Data Preparation View models (yellow-shaded area)

requires hospitalization?. By modeling Insights, characteristics of the machine learning solution were revealed in terms of Type, Input, Output, etc. Such elements are able to demonstrate what the analytics solution would offer for answering questions and addressing analytical needs. The model shows that a **Hospitalization Predictive Model** can satisfy the above-mentioned question and hence support the decision element. It works by receiving the **Patient profile** as input and generates a binary flag of **Event will happen? (Y/N)** as Output.

By creating the Analytics Design View models, the design of the machine learning solution in terms of Algorithms, Metrics, Softgoals (NFRs), and trade-offs was revealed. The model in Fig. 9 shows that the product uses predictive modeling algorithms (**classification**) for serving the analytical needs mentioned above (**Hospitalization Predictive Model**). It shows the Algorithms (e.g., **k-Nearest neighbor**, **Random forest**, **Logistics regression**) that are used in the product and the Metrics (e.g., **Recall**, **Precision**, **F-measure**) that are in place for comparing their performance. It also shows relevant NFRs for the problem at hand (e.g., **Robustness**, **Storage for training model**) and how different algorithms would influence them.

By creating the Data Preparation View models, the design of data preparation and transformation pipelines in the product were revealed. The model in Fig. 10 shows that in order to prepare the **Patient profile** data (required to generate the **Hospitalization Predictive Model**), various data tables,

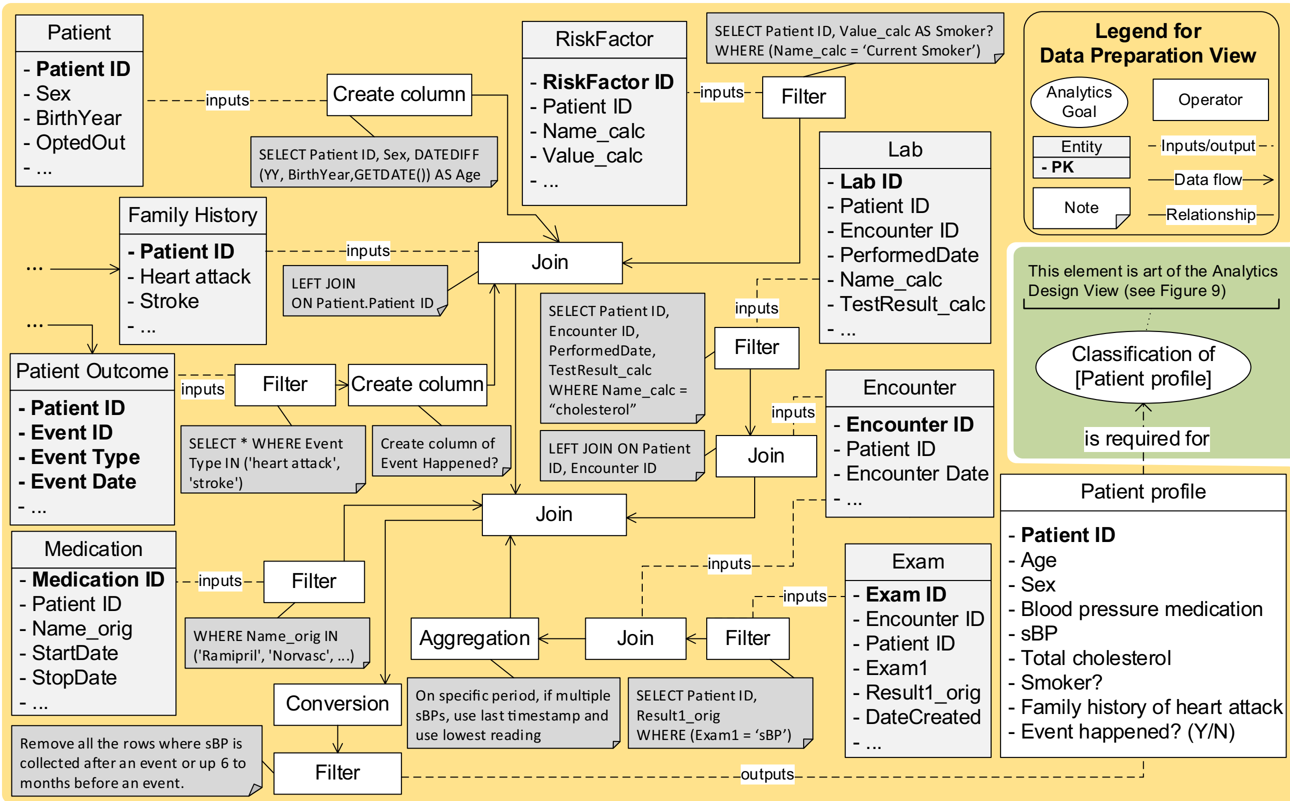

Fig. 10 Data Preparation View Model for the Classification Goal in Fig. 9

including **Patient**, **Exam**, **Medication**, and **Family History** are required. In addition, it shows how different tables are queried, merged, and filtered through the data preparation process**.**

5.2 RQ-2: Usefulness

The case study provides evidence that the framework can be useful in machine learning development projects.

Revealing new machine learning requirements or features for the current product. Through the course of modeling and collaboration with the project team, several new features and extensions to the current analytics product were revealed. The product architect remarked, during the feedback session, pointing to several areas in the models:

> *"I myself would have never thought of that, without going through this modeling exercise."*

During the Business View modeling, new requirements were elicited for each of the stakeholders in the form of Decision Goals, Question Goals, and Insight elements. For example, for **Physician** (Fig. 6), the Questions Goal of **What interventions (top 5) will have the biggest impact on population health risk?** was identified as a new needs-to-know of physicians, whose answer can support the **Decision on treatments** to be prescribed. For **Patient with Chronic Disease** (Fig. 7), in order to make the **Decision on information to share with the doctor**, answering **What information my doctor needs to rule-out suspected conditions?** was identified as a new requirement which the project team had not thought of prior to creating the Business View models. Similarly, for **Government** (Business View model not shown here), the Question Goal of **Which doctors should be included in the program?** was revealed as a new needs-to-know, toward making the **Decision on prevention program structure.**[2] These were seen to be feasible and valuable additions to the current product. In the next modeling view (Analytics Design), such requirements were linked to a machine learning design and later to Data Preparation activities and flows (see Fig. 9 as an example).

[2] Interestingly, recent research in the healthcare domain also supports the idea that enrolling the wrong doctors into government programs can be a contributing factor toward failure of such programs. These research publications were unknown to the modelers and project team during the Business View modeling.

Facilitating communication among project team members. The framework can facilitate and enhance communication among analytics project team members of different roles. During modeling sessions, project team members had discussions around the modeling elements, their links, and their labels (i.e., content).

While modeling the Business View, we observed discussions around inclusion or exclusion of Actors in the model. In particular, the participants discussed inclusion or exclusion of **Government (funder)** as an Actor. This raised discussions on whether or not the product scope includes providing insights and analytics results to government parties. We also observed discussions over the labels of the Decision Goals and Question Goals. In several cases, (e.g., Question Goal of **Will the patient take the medication?** in Fig. 6) this resulted in decomposing the decision or question into lower-level goals. Similarly, while modeling the Analytics Design View, trade-offs between alternative algorithms were discussed. Also, while modeling the Data Preparation View, we observed discussions around inclusion or exclusion of certain attributes in the prepared datasets.

These discussions among participants offer some evidence for the utility of the framework for enhancing communication among different roles within an analytics project.

5.3 RQ-3: Areas for improvement

This section reports on the researchers' observations and feedback obtained in discussion with the product architect (third author) on drawbacks of the framework, along with areas for improvement.

Scoping the business view models. Participants reported that creating the Business View models can be open-ended, labor-intensive, and time-consuming. It would be more efficient to have guidelines and mechanisms for scoping the goal-decomposition, and for ensuring the logical completeness of the model hierarchy. During the modeling sessions, the modelers used typical, prompting questions of "How do you achieve this?" and "How else you could achieve this?" for eliciting lower-level goals. These questions in several cases resulted in a wide range of answers and hence extended the size and complexity of the goal graph. In spite of acknowledging the comprehensiveness of the modeling exercise, the product architect did question the completeness of the model:

> *"I don't know if I have all the use cases. Did I get all the questions? There is no way for me to say!"*

Scoping of the Business View models requires systematic methods and approaches which are not currently developed as part of the framework. Specifically, the framework lacks (formal) decomposition mechanisms for breaking goals into lower-level goals, as well as into decisions and questions. Such mechanisms can serve as a means toward constraining the domain of modeling and hence reduce the effort and time required to construct business view models.

Part of this observation can be attributed to the fact that researchers (here in the role of modelers) had deliberately been blinded to the case domain, its product and focus. The modeling was performed with absolutely no document review, website review, or any assumptions about the company product or its market offerings. In real projects, it is expected that by analyzing existing documents and reviewing process and data models, modelers can have a better scoping of the project. Industry-specific standard models and design patterns were also suggested by participants as a solution to this issue.

Business goals hierarchies and levels. In addition to scoping guidelines, we observed that it is important to develop guidelines for diagnosing situations where the participants skip several layers or levels of goals and move (too quickly) into detailed, lower-level goals. Lack of such guidelines, can result in inaccurate, incomplete models which can omit the chance of finding new ways of doing things, and hence new analytical capabilities toward meeting those goals.

Guidance for modelers. The competence of the modelers was seen to be very critical and influential during the elicitation process and eventually the results. Modeling interviews and activities were seen to require a specific skillset and expertise on how to conduct such sessions. The kinds and order of prompting questions were seen to be well-prepared by the participants. This is indicative of a risk on how business analysts and new adopters of the framework (i.e., those who were not involved in development of the framework) would be able to use this modeling framework. We reviewed the interview recordings to enhance and extend our list of guidelines by adding those questions that were improvised during the modeling sessions. This can be seen as an area for further improvement for the framework.

Refinement of question goals. We observed situations where a Question Goal can be too broad and generic, such that multiple Insight elements can become relevant to the requirement. Question goals that are not sufficiently granular can result in defining the wrong Insight element which itself can lead to designing irrelevant Analytics Design View models. The framework requires certain guidelines and stopping criteria for refinement of Question Goals. Also, iterating between questions (from Business View) and prepared data tables (from Data Preparation View) was found to be a necessary activity to be added to the usage methodology of the framework. We observed that after reviewing an Insight element (especially the Input and Output data attributes), participants may modify and refine a question goal.

Linking the three views through insight elements. We observed that the modeling of Insight elements, as the last activity of creating Business View models, would naturally lead into the starting activities for the other two modeling views. The Insight element is thus a critical element which can be placed in the middle of the three views to link them together. This observation would imply the need for certain extensions to the methodological steps that were previously proposed in [16]. The methodology in [16] provides separate set of activities for each of the three modeling views but does not provide guidance on how to start the modeling activities of the other views.

Prioritizing and analyzing impact of requirements. Participants reported that the framework can be enhanced by including a mechanism or method for modeling the potential impact of different requirements on business. They reported that the framework revealed many valuable Questions Goals; however, it did not provide support for prioritizing and ranking them based on business value that they would offer. The product architect desired more guidance on connecting model concepts to potential revenues for communication to senior management.

> *"There were many questions that were brought up, but to be able to prioritize them and say oh this is the one that will generate more value for the customer is missing. It generates hypotheses, but it does not give you definitive answers. We need it to tie it to financials."*

Here, Indicators from the Business View were considered to be a necessary modeling element for tracking goal achievements and changes over time; however, the framework lacks techniques for projecting/forecasting the impact of various machine learning requirements on different Indicators. This can get more relevant and powerful if the causal impact of indicators within (and among) actors can be modeled and reasoned about.

> *"As a doctor, it takes me 10 s to make some decisions about patients. If you speed that up, would there be benefit in it? Maybe, maybe not. I read a paper that says AI actually slows radiologists' work … Obviously it was implemented incorrectly."*

Participants reported that by equipping the framework with such mechanisms, it would enable future adopters to prevent scenarios where implementing machine learning solutions (incorrectly) can negatively impact business (e.g., slowing down certain processes).

Structure and replicability of the approach. The project team found the modeling methodology adopted for this case study (the top-down approach) to be a well-structured approach, in the sense that it starts with business Goals and decomposes them to Decisions and Question goals toward Insights and thereafter to machine learning design and data preparation pipelines. They found the prompting questions (used by modelers in each step, see "Appendix A") to be an effective way for leading and navigating through the steps. The product architect reported that the modeling activities were easy to replicate and not complicated.

> *"Once you do it a few times, you get a good sense of how this process is done. At the beginning I was like, 'What is this?'"*

While appearing to be abstract and unclear at the beginning, participants reported that after seeing how different elements are modeled and linked for a few actors, they started to think in the same way, which is different from their previous way of looking at machine learning initiatives. They reported that prior to seeing this framework, their thought process was more bottom-up, starting with machine learning algorithms while trying to find a problem to use it for, or to apply it to a known (assumed) problem.

> *"Now, when I start to think about ML, I ask myself what is the goal here? Before I was starting from down here* (pointing to leafs of a Business View model)*, trying to figure where it is going."*

Seeing the framework in action changed participants' thought process to a hybrid approach.

5.4 Threats to validity

This section discusses threats to validity of findings based on the criteria suggested in [20]. We describe some potential weaknesses in the study design and outline our attempts toward mitigating them.

External validity. Although the researchers attempted to sample for maximum, the total number of cases was limited to one case belonging to one domain (i.e., health care). This was mainly due to the constraints that were imposed by the selection criteria. In order to reduce the impact of this threat, the researchers tried to collect and provide multiple lines of observations and evidence for each of the findings.

Reliability. In this study, researchers (i.e., the creators of the framework) played the role of modelers and applied the framework. This can potentially introduce researcher bias into the findings and impact their generalizability. In order to reduce that bias, until the end of modeling activities, any details about the case such as the analytics solution, its features, customers, and datasets were deliberately kept unknown to the researchers. In addition, the researchers avoided any access to publicly available information on the company's website, product demos and presentations throughout the modeling activities. Moreover, during the elicitation activities, the modelers took a passive role and merely focused on creating models as result of answers they received with respect to prompting questions and templates.

Construct validity. The first two research questions are focused on expressiveness and usefulness of the framework.

These constructs are subjective and qualitative in nature and can have different meanings for different researchers. There can be a variety of criteria and variables that one can use to analyze and evaluate the expressiveness and usefulness of a modeling language. Regarding expressiveness, this study focused on showing that modelers arrived at a characterization of the machine learning solution in three views. It showed that modelers were able to reveal details that were (deliberately kept) unknown to them prior to the study. Regarding usefulness, this study focused on showing that by going through the modeling activities, new requirements can be elicited and agreed on as new product features, while communication and common understanding among different roles can be facilitated.

Internal validity. During modeling sessions, the first two authors simultaneously played the double role of researchers (collecting observations toward research questions) and modelers (collecting information toward building models). Some sessions were led by the first author only. As a result of multi-tasking in addition to diversity and volume of incoming information, certain critical observations may have been missed by the researchers. To reduce impact of this threat, all the modeling sessions were voice-recorded and reviewed by the first author after each session.

Participants, all belonging to the same team and company, had different seniority levels. As a result, their group dynamics could cause some participants to be more outspoken than others. To address this threat, the researchers tried to encourage all participants to voice their opinions throughout all sessions.

6 Related work

Despite remarkable advances in machine learning algorithms and applications, there has been little attention paid to requirements engineering for the development of machine learning solutions. It has long been recognized that data science projects should include business understanding and problem specification as starting points of solution development. Early works in this domain are those that propose process models for conducting data mining projects [21]. The nine-step model proposed by Fayyad et al. [22] is often considered to be the first knowledge discovery and data mining process model. The CRISP-DM[3] [23] is often considered to be the most widely used methodology for data mining. Common to all these models is a wide recognition of the necessity and importance of business understanding, objectives determination, and problem specification. Nonetheless, these critical tasks are not yet being addressed by systematic methods and techniques from the requirements engineering area.

Some recent work from the conceptual modeling, software engineering, and requirements engineering communities are focused on design and development of machine learning and advanced analytics solutions. Venues such as RE4AI[4] [24] and SEMLA[5] [25] are recently organized to reflect on and discuss such kinds of contributions. The work in [26] outlines challenges and a research agenda for the exploration of non-functional requirements (NFRs) for machine learning-based solutions. The work in [12] illustrates some potential usage of conceptual modeling techniques and methods in different phases of the CRISP-DM methodology. The work in [27] presents initial findings toward characterizing the requirements engineering side of machine learning projects by interviewing four data scientists. Authors in [28] explore and share experiences from elicitation of data analytics requirements in healthcare organizations. In [9], authors present a re-interpretation of the software capability maturity model (CMM) for machine learning development processes and lifecycle management. The work in [29] offers an architecture-centric method for agile development of (big) data analytics systems. These works do not offer a systematic, modeling approach for requirements elicitation and design of machine learning solutions.

Earlier work in the Goal-Oriented Requirements Engineering (GORE) domain has been addressing relevant areas to advanced analytics. Aiming to support adoption of business intelligence technologies, the Business Intelligence Model (BIM) represents an enterprise in terms of key concepts such as Goal, Indicator, Influence, and Situation [30]. It draws upon well-established practices in the business community (e.g., the Balanced Scorecard and Strategy Maps) and offers a range of reasoning and analysis techniques (e.g., [31, 32]). The Business View part of the framework in this paper builds on BIM and extends it with concepts such as Insight, Question Goal, and Decision Goal. These extensions are critical for modeling and representing machine learning requirements. The framework then connects those requirements to elements in the Analytics Design View and Data Preparation View and hence bridges the gap between enterprise strategic goals, machine learning algorithms, and data assets and pipelines.

GORE approaches were also previously proposed for design and development of data warehouse systems. In [33], authors propose a goal-oriented approach for analysis

[3] CRoss-Industry Standard Process for DM.

[4] The International Workshop on Requirements Engineering for Artificial Intelligence (RE4AI).

[5] Software Engineering for Machine Learning Applications International Symposium.

of data warehouse requirements based on an organizational perspective and a decisional perspective. The work in [34] proposes a model-driven, goal-oriented approach for analyzing requirements and deriving multidimensional models of data warehouses. The framework in this paper, being goal-oriented in the Business View and Analytics Design View, focuses on eliciting machine learning requirements, and linking them to organizational goals and decisions on the one hand, and to data tables and data preparation pipelines on the other.

Relevant to the Data Preparation View of the framework, there have been several works on conceptual modeling of Extraction-Transformation-Loading (ETL) processes. The work in [35] provides a metamodel and conceptual representation of ETL activities for early stages of data warehouse development. The work in [36] provides a systematic mapping study of the literature on ETL modeling. The framework in this paper models data preparation activities to represent how the raw data tables are transformed into the prepared dataset, and link that to machine leaning algorithms in the Analytics Design View.

The framework that was studied in this paper was initially presented in [13]. In [15], the authors illustrate some (potential) benefits of that framework in two cases from the literature and white paper documents. In [14], they illustrate the framework in three real-world case studies (two cases were reconstructions of completed projects while the third case was an application of the framework to an on-going machine learning project) and perform a preliminary validation of its expressiveness. In [16], they extend the previous works by providing methodological steps for constructing models in the three views. They discuss limitations and potential improvements of the framework through a case study in which the framework was applied by a participant who was not involved in the development of the framework. As a result of that, a number of guidelines were developed to assist in the use of the framework. In [17], the authors extend the framework for representing generic and well-proven machine learning designs for commonly known and recurring business problems. They test the feasibility, expressiveness, and usefulness of solution patterns for machine learning, in collaboration with an industry partner in the context of business process management. Although these works include some kinds of evaluation and real-world cases, they don't conduct a formal, methodological approach for validating the framework. The work described in this paper uses the case study method to investigate expressiveness and usefulness of the framework in a domain where the framework was not previously applied (the healthcare domain).

7 Conclusions and future work

The development of machine learning solutions involves creating and uncovering well-defined business cases, translating them into machine learning tasks and problems, designing and experimenting with alternative algorithms, model evaluations and trade-offs, and designing data preparation pipelines, among other tasks. Despite the potential value and benefits that requirements engineering techniques can offer throughout this process, not much research has been done in this area. This paper reports on an empirical study that was conducted to evaluate the GR4ML conceptual modeling framework for machine learning solution development for the healthcare sector.

Using a case study approach, this paper investigates the expressiveness and usefulness of the framework, reports the feedback received, and identifies some areas for improvement. The case study provides evidence that the framework includes an adequate set of concepts for expressing machine learning requirements and solution design. The case study also shows that the framework can be useful in machine learning projects, by revealing new requirements that the case participants had not previously thought of before applying the framework, as well as by facilitating communication among project team members of different roles. This study was conducted retrospectively to uncover an existing analytical software product toward addressing the research questions. The goal was not to offer a model-driven methodology for conducting machine learning development projects.

The overall feedback on the framework was positive, especially about the goal-oriented thinking process about machine learning; to start from business goals, refine them into decisions and questions, and thereafter reveal machine learning requirements. Several important areas of improvement were also identified as a result of this study, including lack of guidelines for scoping the goal models in the Business View, and lack of support for prioritizing analytical requirements and for modeling their impact. These findings from the empirical study add to our knowledge on benefits and limitations of the framework outlined in our previous studies.

In earlier work, the framework has been demonstrated primarily in business application settings, including for e-commerce, retail, finance, business process management software, and information technology domains (e.g., [13–17]). There are many opportunities for applying the presented approach and framework in health care. Although we used the framework for addressing important issues in primary care in this paper, it can be expected to offer benefits in other healthcare settings as well. The framework is generic in that it helps planners and implementers to leverage data assets and machine learning capabilities for achieving the goals of an organization. It does this by positing that the goals of an organization ("Improve patient care," "Achieve financial health," "Ensure provider availability") are achieved by making decisions that require answering questions through data-driven insights. Question elements in our framework generally are questions about the state of a patient, a workflow, the capacity of healthcare providers or any other relevant system (e.g., "Does the patient need treatment?", "Is this service sustainable?", "Will we have enough healthcare providers for tomorrow's ER shifts?"). Questions are answered by insights that are extracted using data available in health IT systems ("Patient is at risk of heart attack," "Our costs are higher than our price" or "We're expecting 30% more patients after tomorrow night's baseball game"). Decisions in our framework are interventions that follow from the answer to a Question ("Patient needs prescription for Aspirin," "We need to use a cheaper hip prosthesis in future surgeries" or "We need to increase the number of health providers for tomorrow's ER shift"). Questions, decisions and goals are characteristics of many processes and systems in healthcare settings and other industries. Increasingly, they can be answered or measured using readily available data within the organization's software systems. We believe the framework will be useful to planners, administrators and implementers who can apply this pattern to the management of systems within their domain of responsibility.

Further work is needed to extend and improve the findings and address the threats to validity of this study. That includes conducting studies with a larger number of cases, and ideally in different domains. Modeling sessions in future studies should be conducted by modelers who are not developers of the framework. The expressiveness and usefulness of the framework can be evaluated with different construct definitions and other empirical methods to extend and improve the findings. Other aspects of the framework, including its comprehensibility, can also validated. Future work can investigate applications of goal modeling evaluation techniques for analyzing potential impacts of machine learning solutions on business objectives, and to explore alternative solutions [37]. Such analysis can be further enriched by modeling dependency relationships among actors, as in *i** models [38]. This case study was limited to a top-down application of the framework. Future work will investigate other methodological approaches in applying the modeling framework.

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Appendix A : List of prompting questions for constructing models in the framework

Constructing Business View models

- What are the key business strategies in your domain of interest?
- Who is responsible for/aim to achieve those goals?
- How are they achieving this? How else can we achieve this?
- Why are they doing this?
- What are the key performance indicators in this context?
- How would you measure how well you are achieving those goals?
- What are the business decision(s) that need analytics (or data-driven) support? Who are those decision makers?
- Why would they need to make such decisions? Which business goal is each decision part of? Which business (routine) process is this decision part of?
- What is the frequency of each decision (how often)?
- What would the decision maker(s) need to know during the decision processes?
- What are the questions that come to their mind (and they need to have an answer for) during their decision making activities?
- For each question, if it is too broad, can you break it into sub-questions?
- Specify the tense (past, present, or future), and frequency (how often) of the questions
- From the given list, specify what kinds of answers are needed for each of the business questions? Predictive model, groupings of the data (segments), probability model, diagram (visualization), or logical rules
- For each of the above, specify the Input, Output, Usage Frequency, Update Frequency, and Learning Period of the machine learning model

Constructing Analytics View models

- What kind of analytics (descriptive, predictive, or prescriptive) would be appropriate to generate required insights?
- What algorithm(s) exist for fulfilling the analytics goal at hand?
- What are the quality attributes or non-functional requirements (NFRs) are critical for users?

•What numeric metrics would be used to compare/evaluate the algorithms?
•Define the threshold (upper or lower) values for indicators (e.g., minimum required accuracy for predictive models)
•How are the critical NFRs influenced by alternative algorithms?
Constructing Data Preparation View models
•What kind of data would be relevant for generating the insights and answering the business question at hand?
•What data attributes (i.e., features), in what format, and aggregation level are needed for the question goals under consideration?
•Where is the data stored, and what is data schema (i.e., entities and relationships)?
•Explain, to best of your understanding, the attributes, format, and size of the dataset at hand
•For each attributes, what is the data types, aggregation level, and selection of records (filtering)?
•What (sequence of) integration, cleaning, aggregation, filtering, and other data preparations are needed for transforming the raw data tables into the prepared data tables?
•Are there any data quality concerns?

Appendix B: Questionnaire used for collecting feedback in post-modeling interviews

[Q1] At the end of modeling sessions, were the modelers able to arrive at a characterization of your existing analytics solution/product?

- If your answer is NO, please explain what aspects/parts/components of your product/solution were not identified at the end of modeling sessions.
- If your answer is YES, please provide 2–3 sentences on which area of the graphical models correspond to which part of your product.

[Q2] Through the course of this collaboration, were there any instances of understandings or findings that you and your team were not able to arrive at that prior to the modeling activities? Please provide 2–3 examples.

[Q3] What did you find useful about the framework? (Write 3–4 sentences or bullet points). This can include specific modeling language features or methodological steps, as well as the general approach.

[Q4] What do you think is most lacking in the framework? Are there additions to or variations on the framework that you would like to see?

[Q5] Provide 2–3 examples of features that are not part of current your product/solution, but after the modeling sessions, you think that they can be fruitful additions.

[Q6] What are the aspects or features of the framework that you consider least useful? (This can include modeling language features as well as methodological steps.)

[Q7] In arriving at your current analytics solution/product, you had evolved the product conception and design through one or more iterations in the past. Retrospectively, do you think using the modeling framework would have enabled you to arrive at a viable product more easily or sooner?, e.g., in uncovering pain points and analyzing failure stories and scenarios, and in providing guidance and focus in the search for solutions.

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