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RESEARCH PAPER

The New Era of Business Intelligence Applications: Building from a Collaborative Point of View

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Abstract Collaborative business intelligence (BI) is widely embraced by enterprises as a way of making the most of their business processes. However, decision makers usually work in isolation without the knowledge or the time needed to obtain and analyze all the available information for making decisions. Unfortunately, collaborative BI is currently based on exchanging e-mails and documents between participants. As a result, information may be lost, participants may become disoriented, and the decision-making task may not yield the needed results. The authors propose a modeling language aimed at modeling and eliciting the goals and information needs of participants of collaborative BI systems. This approach is based on innovative methods to elicit and model collaborative systems and BI requirements. A controlled experiment was performed to validate this language, assessing its understandability, scalability, efficiency, and user satisfaction by analyzing two collaborative BI systems. By using the framework proposed in this work, clear guideless can be provided regarding: (1) collaborative tasks, (2) their participants, and (3) the information to be shared among them. By using the approach to design collaborative BI systems, practitioners may easily trace every element needed in the decision processes, avoiding the loss of information and facilitating the collaboration of the stakeholders of such processes.

Keywords Collaborative systems · Business intelligence · Goal-oriented requirements · CASE support · I-Star · Controlled experiment

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1 Introduction

In recent years, business intelligence (BI) has focused on providing better and more useful information to decision makers aimed at improving the decision-making process. However, a decision maker working in isolation can only make precise and informed decisions within his/her expertise field and time frame. In order to make a decision that requires going beyond one's expertise or available time, decision makers should collaborate with those able to cover their weaknesses. As an example, let us consider a CEO who needs to develop a statistical model to analyze customers' habits in order to explain a recent rise or drop in the sales of the company. This would require the CEO to have sound technical and statistical abilities and sufficient time to spare after his other tasks. Unfortunately, this scenario seems unlikely.

Current practices for collaborative scenarios in BI are very simple: decision makers communicate and share data with others by sending and receiving e-mails, spreadsheets, and so on (Berthold et al. 2010). Therefore, information may be lost, participants may become disoriented and, consequently, the decision-making process would yield poor results. Indeed, in order to address these problems, BI tools can benefit from the advantages that Computer Supported Cooperative Work systems provide (Schmidt and Bannon 1992), such as the remote collaboration of different stakeholders who are able to provide knowledge in real-time to foster the decision-making process. Moreover, the introduction of awareness information (Gutwin and Greenberg 2002; Gross 2013) in this shared workspace will enrich the collaborative decision-making process, thus making stakeholders aware of who has the required knowledge to make a decision, or their availability for real-time discussions on decision-making.

Recent research has focused on developing novel support for collaborative decision making within BI platforms. From sharing data (Rizzi 2012) to creating virtual rooms (Berthold et al. 2010), different approaches try to provide tools that enable decision makers to jointly use the required information in a more ordered and easier manner. Nevertheless, up to now, no approach has been proposed that provides designers with expressive power to model collaborative tasks as well as the information needed to carry them out, thus providing adequate support for these tasks. In this context, the first goal of this paper is to propose an extension of CSRML4BI, a goal-oriented framework that enables BI designers to model and elicit both the participants' requirements in individual and collaborative BI tasks. This revised version will thus address the shortcomings of the already existing version (Teruel et al. 2012, 2014), by adding the following features.

New modeling elements: several elements and relationships have been added to the language in order to make a more complete specification of collaborative BI systems.

New awareness model: the previous awareness model has been replaced by a far more comprehensive one which will not only enable us to model more present and past awareness requirements, but will also include elements related to the future or to social aspects.

Model organization in diagrams: this extension of CSRML4BI now enables us to divide the collaborative BI system specification into five different diagrams, which will improve the understandability and readability of the generated models.

Comprehensive formalization: the CSRML4BI metamodel has been revised and extended, thus including the new modeling elements, as well as the multi-diagram support.

CASE support: together with this extension of CSRML4BI, a CASE tool has also been released in order to facilitate its usage.

Empirical evaluation: CSRML4BI was empirically evaluated by means of a controlled experiment in order to assess its suitability.

Therefore, thanks to our approach, designers can (1) accurately identify which participants need to communicate with each other, (2) why, and (3) what information they need to share. Therefore, we can plan how the system will support collaboration in the Requirements Engineering stage of the Software Development Process (Pressman 2009; Pohl 2010). Our framework is based on recent approaches proposed for modeling both business intelligence requirements (Maté et al. 2011) and collaborative systems.

The second goal of this study consisted of evaluating the proposed CSRML4BI extension. For this, we performed a controlled experiment where our participants analyzed two collaborative BI systems modeled with CSRML4BI and *i** (Yu 1997).

The rest of this paper is organized as follows: Sect. 2 looks into the related work on collaborative BI and decision-making as well as on BI requirements collaborative modeling. Section 3 presents our framework, depicting the metamodel and introducing new elements. Section 4 describes the controlled experiment that was performed to evaluate our proposal. Our conclusions and future work are outlined in Sect. 5. ''Appendix A'' (available online via springerlink.com) describes a collaborative BI system modeled by CSRML4BI.

2 Related Work

The amount of information available has been continually increasing in recent years. Social Media analysis (Asur and Huberman 2010; Oh et al. 2013), Big Data (Zikopoulos et al. 2011; Embley and Liddle 2013) and Open Data initiatives (Lakomaa and Kallberg 2013; Oh et al. 2013; Lindman et al. 2013) have driven the increased interest in collaborative BI (de Moor 1999; Kaufmann and Chamoni 2014), as isolated decision makers and analysts no longer have sufficient knowledge to make a decision with confidence.

In a survey of the area, covering several approaches on collaborative BI, we can establish three well differentiated groups (Kaufmann and Chamoni 2014). Most existing approaches (Dayal et al. 2008; Berthold et al. 2010; Devlin 2012) understand collaborative BI as a technology-driven development, i.e., the enrichment of existing BI systems by communication tools. These are classified as *internal communication* (IC) approaches. A relevant example is presented by Berthold et al. (2010), who propose an architecture for a BI platform that supports collaboration, including collaboration rooms where decision makers can jointly analyze dashboards and charts while they are aware of the presence and actions of other decision makers. On the other hand, collaborative BI systems focus on *partnership in data* (PD) where external partners are involved in the process of data provision. The approach proposed by Golfarelli et al. (Golfarelli et al. 2012; Rizzi 2012) presents the *business intelligence networks* (BIN) concept. In this scenario, every network participant can share and query information from other participants in the network by using mappings between information schemata. The third group revolves around *partnership in analysis* (PA) (Mettler and Raber 2011; Liu and Daniels 2012), i.e., the collaborators work together in the data analysis process. Mettler and Raber (2011) propose an architecture based on a central data warehouse, where suppliers and manufacturers can collaborate to manage the purchasing of supplies and the manufacturing process.

All these technical advances facilitate the application of collaborative BI. However, there is a need for an approach that helps BI system designers to elicit and model the requirements of BI systems whose final users must collaborate in order to achieve the system's goals.

As far as collaborative system requirements modeling is concerned, CSRML (Collaborative Systems Requirements Modeling Language) was presented in (Teruel et al. 2011a). CSRML is a language that expands the expressive capabilities of *i** (Teruel et al. 2012) in order for analysts to specify the requirements of collaborative systems. Another language, based on XML, for User Interfaces (UI) design has been also proposed (Figueroa-Martinez et al. 2013) and extended to support collaborative information requirements. Both languages were designed for all-purpose collaborative systems and thus lack the detail that data warehouse and BI requirements modeling approaches, such as Giorgini et al. (2008) and Maté et al. (2011), provide. These latter approaches are also based on *i**.

On the other hand, BI requirements modeling approaches (Giorgini et al. 2008; Maté et al. 2011) enable us to capture the rationale of individual decision makers, including the information that BI systems must store to support the decision-making process. However, they are unable to describe collaborative tasks and their characteristics, including the kind of collaboration and workspace awareness required for each task. As a result, although these approaches are more suitable for modeling BI systems, they lack adequate constructs for modeling collaborative BI requirements.

It is noteworthy that modeling approaches can benefit from several goal-reasoning techniques (Giorgini et al. 2003, 2005; Horkoff and Yu 2010). Decision makers may exploit goal-reasoning to ask important questions about the system related to their models, such as (1) goal priorities, (2) implementation alternatives, or (3) which stakeholder needs can be satisfied. In order to provide answers to such questions, goal-reasoning techniques require that modeling languages are complete with respect to the concepts of the domain. Therefore, before obtaining interesting knowledge, our modeling language must be able to adequately represent all the relevant elements involved in a collaborative decision process, thereby reinforcing the need for a dedicated language that captures all the relevant aspects of collaborative BI.

In short, current advances in collaborative BI would benefit greatly from a modeling language that system designers could use to capture the requirements of this type of information system, including their collaborative aspects. However, due to the idiosyncrasy of collaborative BI, current requirements modeling proposals fall short of achieving this end.

3 CSRML4BI: An Improved Modeling Language for Collaborative Business Intelligence

Throughout the literature, one can find applications of goal-oriented requirements modeling for different domains, such as adaptive applications (Vitali et al. 2015) or data warehouses (Maté et al. 2011). However, when dealing with systems that entail the specification of collaboration, current goal-oriented approaches lack the expressive power needed to deal with this feature properly (Teruel et al. 2011b). Because of this, CSRML (Teruel et al. 2012) was chosen as the foundation of our proposal, since it is used to specify collaborative tasks as well as groups of actors, while specifying the system from a decision viewpoint. CSRML also supports awareness modeling characteristics, enabling the system designer to specify what the stakeholders must be aware of to collaborate properly. In this regard, CSRML enables us to model awareness requirements such as where the participants are working, what they are doing, who has a certain piece of strategic information, or when a decision was taken.

In this scenario, CSRML4BI is a Goal-Oriented Requirements Engineering language designed to model collaborative BI requirements, in the form of an evolution of its previous definition (Teruel et al. 2011a). It also introduces new constructs that may be used by designers to perform the elicitation and specification of information requirements requiring the collaboration of single or multiple decision makers. These new constructs defined in this new version of the CSRML4BI metamodel are highlighted in red in Figs. 1, 2 and 3.

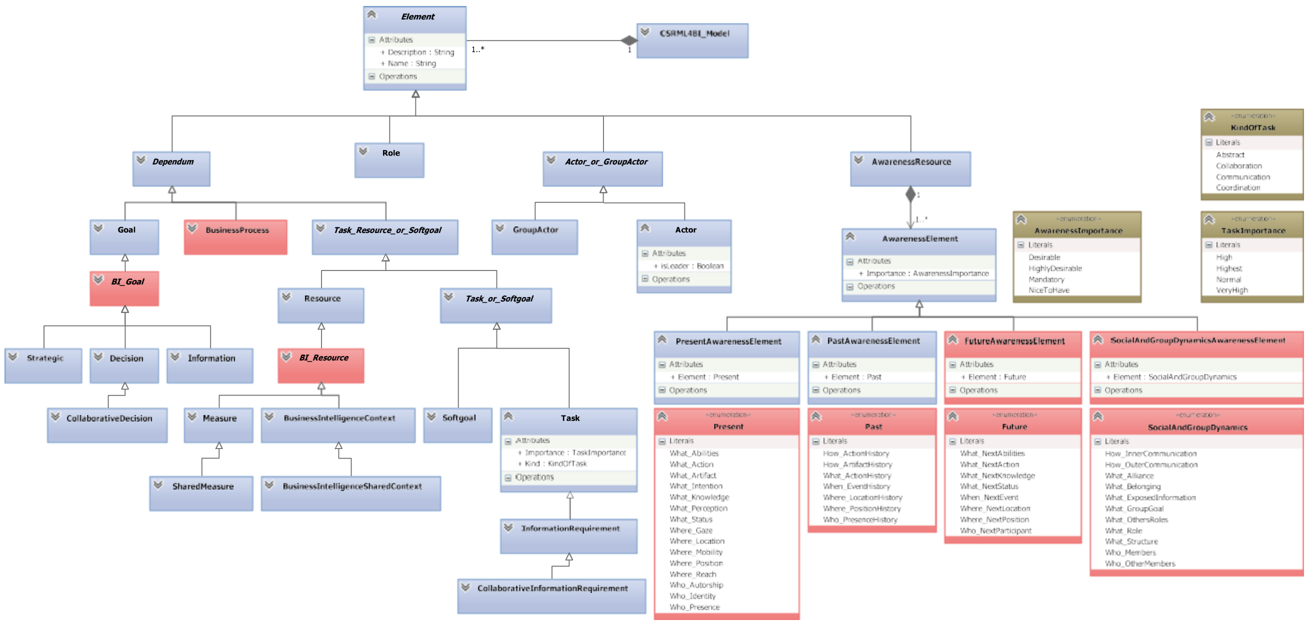


Fig. 1 CSRML4BI metamodel (elements) (color figure online)

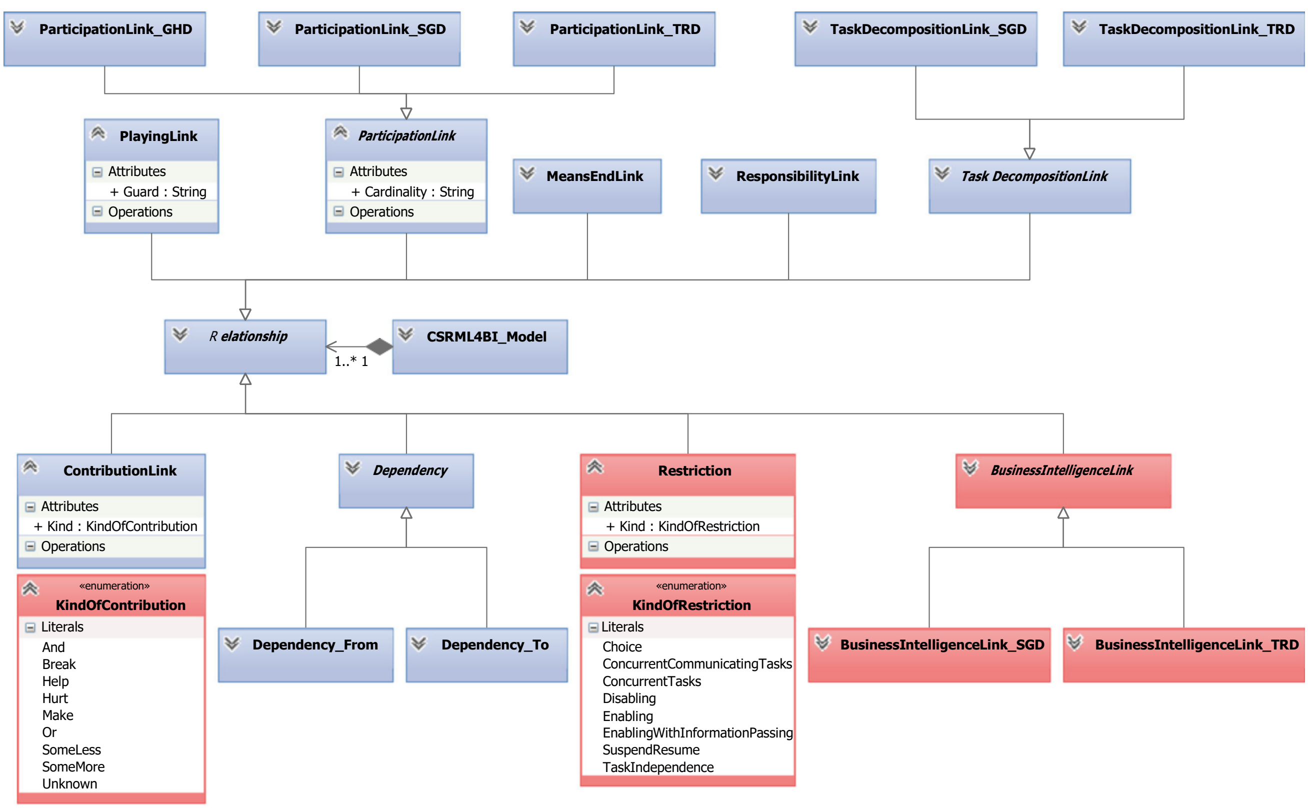


Fig. 2 CSRML4BI metamodel (relationships) (color figure online)

It is worth noting that CSRML4BI involves a top-down modeling approach (see Fig. 4). For this reason, the system specification begins with the identification of its participants, after which the main BI goals of the system are specified. Next, the conditions for participants (actors) to play certain roles are defined, as well as their

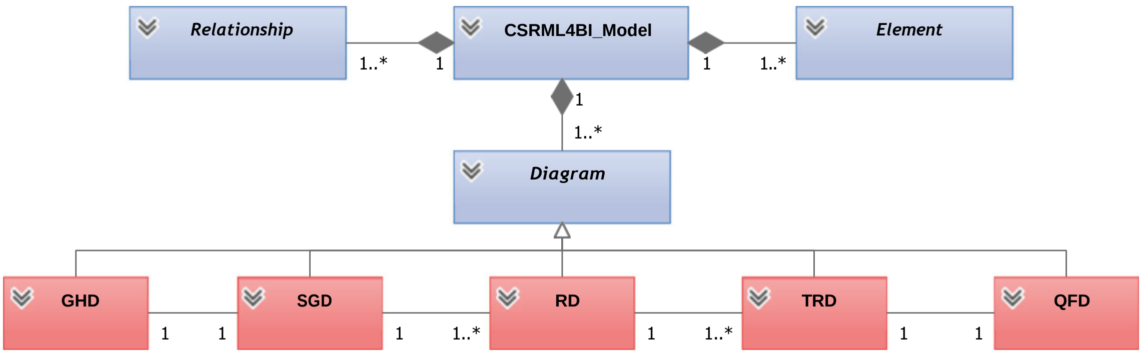


Fig. 3 CSRML4BI metamodel (diagrams) (color figure online)

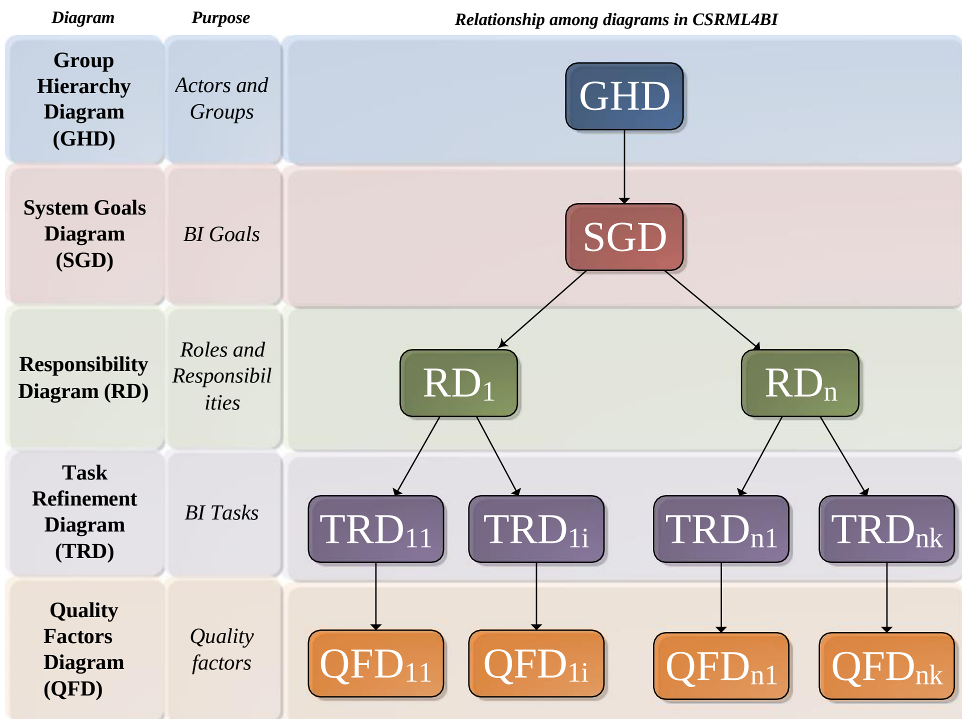


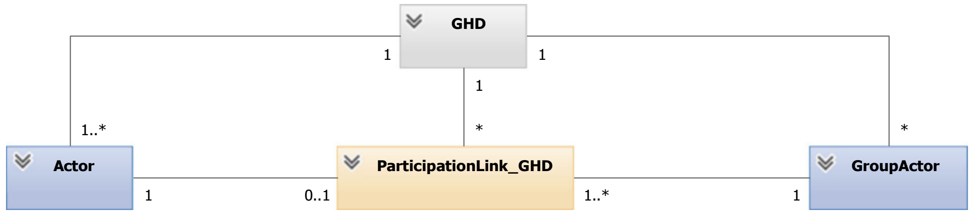
Fig. 4 Purpose and relationships among CSRML4BI diagrams

responsibilities. The system task definitions, the cornerstone of the BI system specification, are obtained by defining how the different participants must collaborate, as well as what they have to be aware of to collaborate. Finally, the necessary quality factors are defined.

Not only new modeling elements have been added to the language, but also the previous awareness model in CSRML4BI (Gutwin and Greenberg 2002) has been extended to also consider future and social awareness needs (Teruel et al. 2016) (see Sect. 3.4). A CASE tool was also developed to facilitate the modeling process with this new language (see Sect. 3.6).

As in CSRML, CSRML4BI promotes the specification of the requirements of collaborative BI systems by means of 5 different types of diagram to improve the readability and understandability of the specification. These diagrams will be described in Sects. 3.1 to 3.5, along with the elements and relationships shown in the above metamodel. A running example will be used to show how to specify a collaborative BI system with CSRML4BI in ‘‘Appendix A’’, and will include concepts from Kelly et al. (2004).

Fig. 5 GHD metamodel



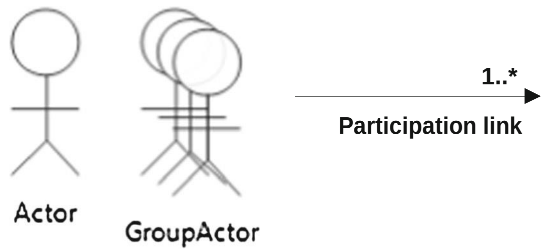


Fig. 6 Graphical representation of GHD's elements

3.1 Group Hierarchy Diagram (GHD)

The Group Hierarchy Diagram (GHD) (Fig. 5) depicts the different stakeholders (and their groups) involved in the BI system. Considering that CSRML4BI has user collaboration as one of its main cornerstones, *Actor*, *GroupActor* and *Participation Link* have been described as follows.

- *Actor:* these can be either users, programs, or entities with certain acquired capabilities. They can play a role in executing an action, using devices or being responsible for actions. Actors can play one or more *roles* regarding the information system that is specified.
- *GroupActor:* this designates a group formed by one or more actors who aim at achieving one or several goals. Therefore, by using these elements, groups of users can be specified. Unlike what happens with the *Role* concept (Sect. 3.3), a GroupActor is static. That means that an actor will always be part of the same GroupActor.
- *Participation Link:* this relationship is used to assign an actor to a GroupActor (see Fig. 6). Its cardinality established how many actors constitute each GroupActor.

3.2 System Goals Diagram (SGD)

A System Goals Diagram (SGD) (Fig. 7) is used to identify the goals of a BI system. Each of these goals will be assigned to the *actors* and *GroupActors* necessary for their achievement. The actors participating in the system-to-be can have one or more *Goals*. In BI requirements modeling, informational goals (Mazón et al. 2007) are refined into different kinds of BI goals, as opposed to traditional goals, which result in *Strategic Goals*, *Decision Goals and Collaborative Decision Goal*. Taking into account the high number of goals, the new version of CSRML4BI simplifies the diagram by specifying only those *Actors* who are responsible for fulfilling each *BI Goal*. The same actor is also responsible for the remaining non-collaborative

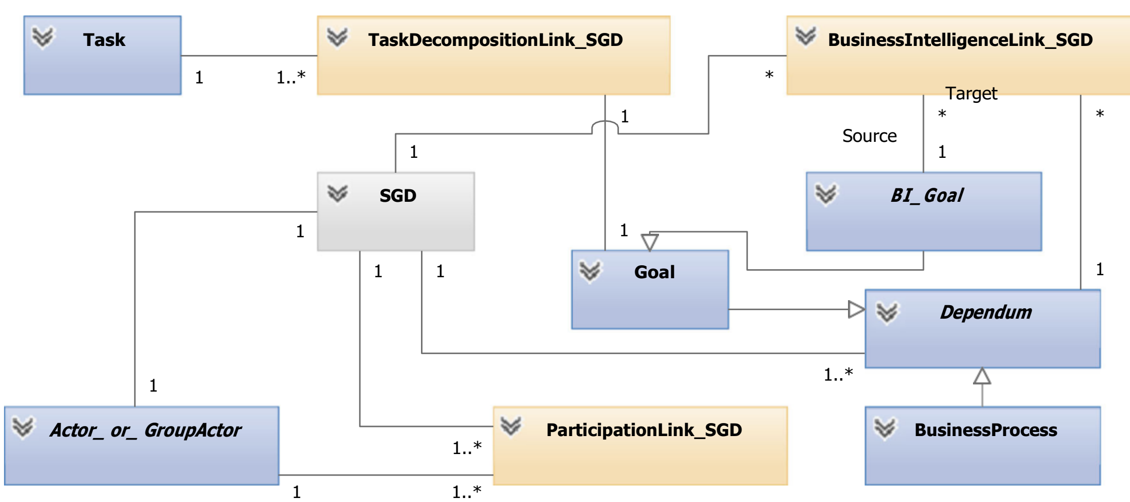


Fig. 7 SGD metamodel

informational goals derived from it. Therefore, the most relevant elements and relationships in an SGD are the following.

Business Process: it represents business activities that decision makers need to analyze to improve results and thus business performance.
Goal: answering ''why?'' questions, this element describes a state that an actor wants to achieve. Nevertheless, goals do not specify how this state should be achieved. As mentioned above, there are 4 specializations for BI goals:

- *Strategic Goal (S):* goals associated with one or more decision makers aiming at improving a *Business Process* within the enterprise. It represents the highest level of abstraction in informational goals and gives an immediate benefit to the organization when achieved.
- *Decision Goal (D):* it tries to answer the question ''How can a strategic goal be achieved?'', and represents decisions for taking actions that contribute to achieving a strategic goal. Decision goals are only specified in relation to a strategic goal and do not provide any profit to the organization on their own. *Collaborative Decision Goals* are specializations of such goals.
- *Collaborative Decision Goal (CD): Decision Goals* require the *Collaboration* or *Coordination* of several *Actors* for their achievement. They represent decisions that must be made by a group instead of a single person.
- *Information Goal (I)*: it answers the question ''How can a decision goal be achieved in terms of the required information?''. Its fulfillment helps to achieve one or more decision goals. Such information goals are located within the context of a decision goal.

Business intelligence link it represents non-*i**-standard decompositions among BI goals (see Fig. 8).

Participation link: it is used to specify which actors are involved in the accomplishment of the system's main goals. The number of occurrences of each actor or group actor is denoted by the cardinality field (see Fig. 8).

Several elements in the metamodel illustrated in Fig. 7 (*Task* and *Task Decomposition Link*) will be described in Sect. 3.4.

3.3 Responsibility Diagram (RD)

Each Responsibility Diagram (RD) (Fig. 9) represents one of the tasks identified in the SGD. The RD specifies the roles played by the actors (under certain guard conditions) and the tasks that the actors are responsible for. Such actors can play either one or more *Roles* while interacting with the system so that the same actor can be considered in a different manner depending on the role played. The following elements can be found in RDs.

Role: it designates a set of correlated tasks to be performed by an actor. Hence, when an actor plays a role, he/she may participate in both individual and collaborative tasks (by means of *participation links*) and may assume the responsibility to achieve a goal (by means of *responsibility links*). Roles can change dynamically (unlike Group Actors, whose Actors are always the same). An Actor can play different roles depending on which guard conditions are satisfied.
Playing link: it is employed to represent an actor who is playing a role. These links have a *guard* condition (Fig. 10) that represents what conditions must be satisfied so that a role can be played by an actor.
Responsibility link: this link is used to assign roles (played by actors) to goals, softgoals, or tasks (see Sects. 3.4 and 3.5). This link represents which stakeholder is responsible for a goal/task accomplishment.

3.4 Task Refinement Diagram (TRD)

In a Task Refinement Diagram (TRD) (Fig. 11), the tasks previously identified in RDs are decomposed into

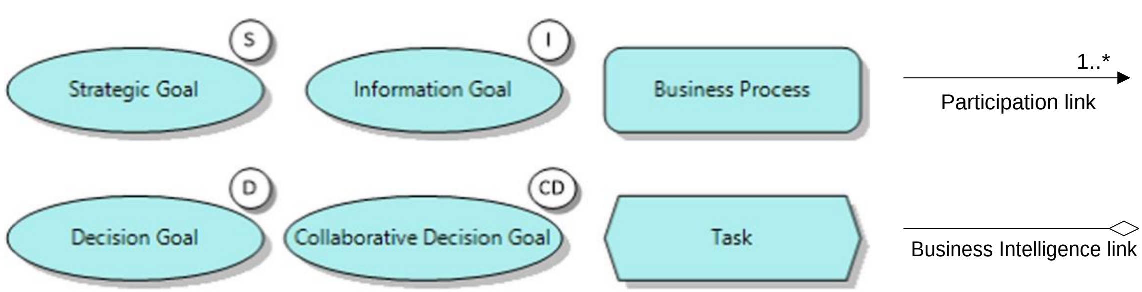


Fig. 8 Graphical representation of SGD's elements

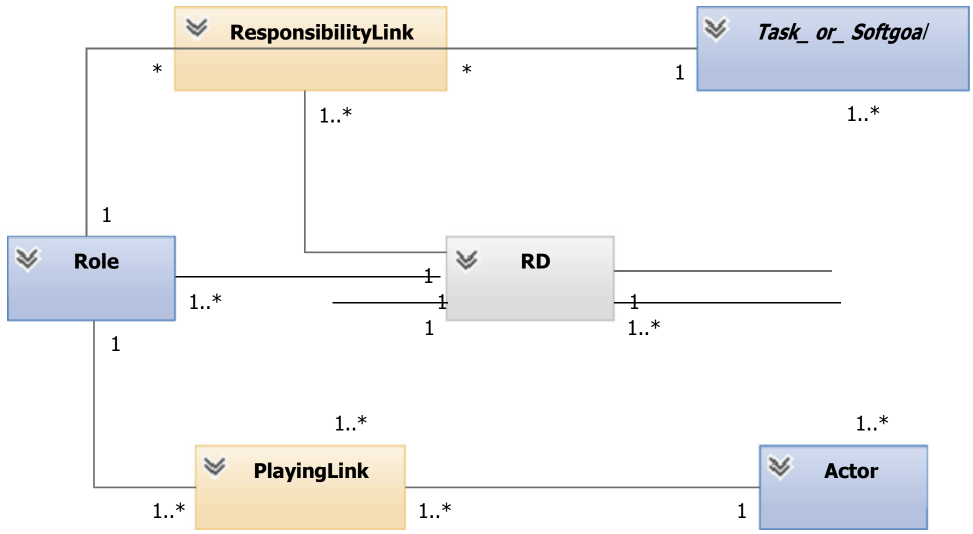


Fig. 9 RD metamodel

Fig. 10 Graphical representation of RD's elements

individual and collaborative tasks that support awareness features. In order to achieve the different information goals, decision makers need to perform certain analysis tasks using information provided by the information system. In our approach, we specify this type of task by means of the refined concept *Information Requirement*, used to describe both analysis tasks to be supported and the information to be provided by the system which is being designed. CSRML4BI identifies the following elements in a TRD.

Task it represents actions that an actor wants to execute, usually with the purpose of achieving a goal. These tasks are hierarchically refined into subtasks up to leaf-level tasks, which define system requirements (Dalpiaz et al. 2016). As shown in the metamodel (see Fig. 1), this element has an importance level according to the task's development priority. This importance is defined by a graphical notation (Moody 2009) based on a color code (green, yellow, orange, red), green being the least and red the most important. The task concept is refined for the BI domain into:

- *Abstract task:* this is an abstraction of a set of concrete tasks and other elements.
- *Concrete task:* this is a refinement of an abstract task and related to roles responsible for its accomplishment. There are four types of concrete task: an *Individual task* that an actor can perform without any kind of interaction with other actors; *Collaboration/Communication/Coordination tasks* that require two or more actors to be involved in order to perform any kind of collaboration/communication/coordination.
- *Information Requirement:* this represents the analysis of information that a decision maker will perform in order to satisfy the corresponding *Information Goals.* They can be decomposed into several *Information Requirements*, *Business Process Contexts* and *Measures*, necessary to support the decision-making process. *Collaborative Information Requirements* are specializations of such requirements.
- *Collaborative Information Requirement: Information Requirements* used by the decision makers to satisfy the *Information Goals* along with the collaboration of other actors. They can (1) simply represent the *involvement* of another actor without further consequences for the analysis, as when information is shared; (2) specify *Communication*, where one or more *roles* have to communicate, such as when decision makers request information from analysts or managers; (3) specify *Collaboration*, where all the *roles* involved interact with each other during the analysis; or (4) specify a *Coordination*, where every *role* involved has to coordinate its analysis task.

Resource: a resource is considered as an entity (either physical or informational) required by actors for

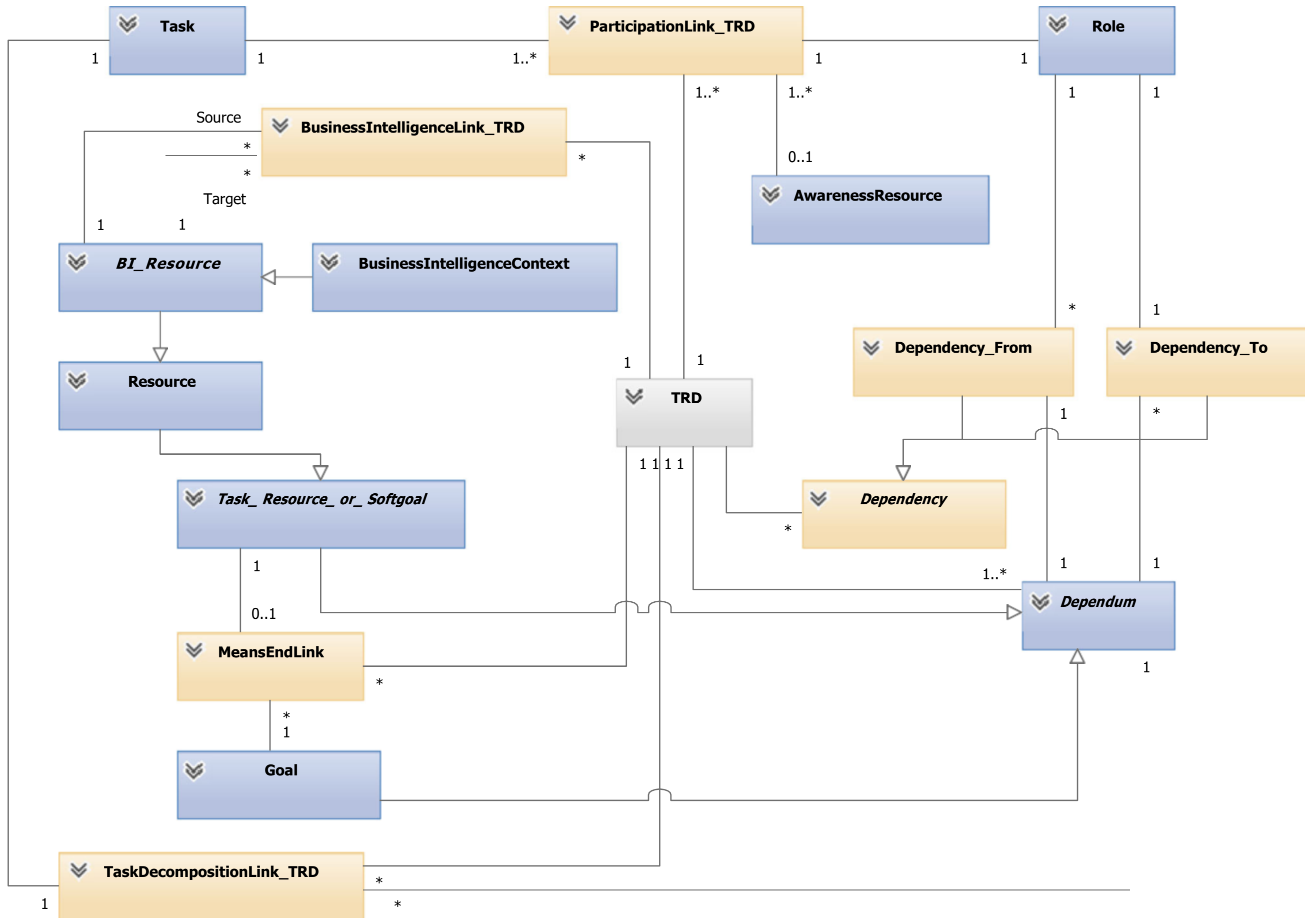


Fig. 11 TRD metamodel

achieving goals or performing tasks. The main interest when specifying resources is whether they are available and from whom. To properly specify collaborative BI systems, the following specializations may be used (see Fig. 12).

- *Business Process Context (BPC):* this represents information about a certain entity which needs to be specified and provided by the system to ease the analysis of business processes from a certain viewpoint. It can be aggregated into other *Contexts*, thus forming an analysis hierarchy which will be implemented in the information system being specified. *Business Process Shared Context* is a specialization of Context.
- *Measure (M)*: it is used to specify numerical information that somehow it can be used to estimate the throughput of the business activity under study, as well as to specify the needs that have to be recorded in order to empower the analysis. *Shared Measure* is a specialization of Measure.
- *Business Process Shared Context (BPSC)*: it represents entity information that is provided to the system by an *Actor*, instead of being gathered by the system itself. Consequently, the supplier is responsible for providing this information.
- *Shared Measure (SM)*: it represents numerical information related to a certain activity that an *Actor* provides to the system. Its supplier is responsible for the existence of this information.

Awareness Resource: it represents a perception requirement that helps a role to perform a task by providing the needed awareness. It includes a set of attributes attached to a *participation link* between a task and the role performing it. Note that this kind of element is depicted in the diagrams in two different ways: the expanded and reduced form. In its expanded form, the Awareness Resource shows all the Workspace Awareness features identified in (Teruel et al. 2016) that can be set (if needed) with their importance according to the contribution to the accomplishment of a task (see Fig. 12). These awareness features are categorized into four

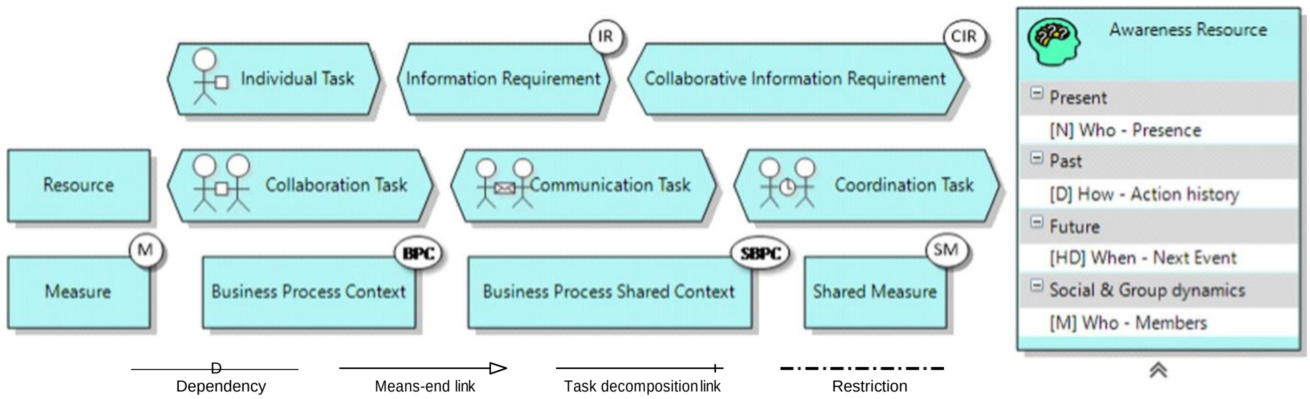


Fig. 12 Graphical representation of TRD elements

sections, related to present, past, future and social awareness needs, like in (Teruel et al. 2016). The importance of each awareness element can be *nice to have* (N), *desirable* (D), *highly desirable* (HD) or *mandatory* (M).

Dependency: dependencies are relationships between a depender and a dependee to achieve a dependum. Both depender and the dependee are roles played by actors. Dependums can be either goals, tasks, resources or softgoals. Hence, dependers depend on dependees to achieve goals, to perform tasks or to use resources. If the dependee does not provide the depender with the dependum, it may be difficult or even impossible for the former to achieve a goal, perform a task or use a resource. According to the kind of the dependum, 4 types of dependencies can be found: goal, task, resource or softgoal dependencies.

Means-end link: means-end links define whether a softgoal, task, and/or resource contributes to achieving a goal. These links also ease documentation and evaluation of alternative ways to satisfy a goal (Horkoff and Yu 2012), that is, they are used to specify different ways of decomposing goals into several subgoals, tasks or resources.

Task decomposition link: it depicts the fundamental elements of a task. Task decomposition links relate a task to its components. Such components can be any combination of goals, tasks, resources, and softgoals. The decomposition of a task can comprise sub-tasks that have to be performed, sub-goals that have to be achieved, resources that can be needed, and softgoals that usually define quality goals for such a task.

Participation-link: it defines which role is involved in the performance of a task. These links have an attribute to specify cardinality, i.e., the number of users that can be involved in a task. It may be optionally related to an awareness resource for specifying that the role involved has a special perception requirement (specified though an awareness resource) to participate in a task. Without this awareness information, the performance of the task could be negatively affected or the role will not be able to participate in its accomplishment.

Restriction: it represents a temporal restriction between two tasks following the UsiXML style (Limbourg et al. 2004). These temporal restrictions (and symbolic representation) can be:

Enabling ( ): it specifies that the second task will not begin unless the first task is performed.
Choice ([]): it defines that once a task starts, the other task is no longer enabled.
Enabling with information passing ([]▮): it defines that the second task cannot be performed until the first one has been carried out, using the output information of the first task as input for the second.
Concurrent tasks (|||): they define the likelihood of performing tasks in any order, even at the same time. It is also possible for a task to start before the other task is finished.
Concurrent communicating tasks (|[]|): they specify that the related tasks can share information while they are performed concurrently.
Task independence (|=|): it defines that the related tasks can be performed in any order. However, when one task has started, it has to finish before the other can begin.
Disabling ([▮): it specifies that the first task (commonly an iterative task) is entirely interrupted by the second.
Suspend-Resume (|▮): it defines that the first task can be interrupted by the second. Hence, once the second terminates, the first one can be reactivated from the previously reached state.

Examples of several of these restrictions can be found in Fig. 28 (''Appendix A'').

There are several ways to achieve system goals. For example, individual users may use the system in isolation, or decisions may involve multiple decision makers, requiring not only business process related information but also requiring the system to be context-aware (Martínez-Carreras et al. 2013).

3.5 Quality Factors Diagram (QFD)

A Quality Factors Diagram (QFD) (Fig. 13) specifies the quality factors that contribute to achieving the softgoals (quality factors) and tasks identified in RDs and TRDs. Therefore, these diagrams are used to specify the non-functional part of the system (Zhu et al. 2012) by using softgoals. As a novelty, the following elements may be specified in these diagrams (Fig. 14).

Softgoal is a state that an actor wants to achieve. Nevertheless, unlike (hard) goals, the condition for the achievement is not well-defined. Hence, a softgoal is typically an attribute related to the system's quality that constrains other elements, such as goals, tasks or resources.

Contribution link depicts an influence from a task or softgoal to a different softgoal. It is defined by means of some of the following types of attribute:

Make: a positive contribution strong enough to fulfill a softgoal.
Some ?: a positive contribution with unknown strength.

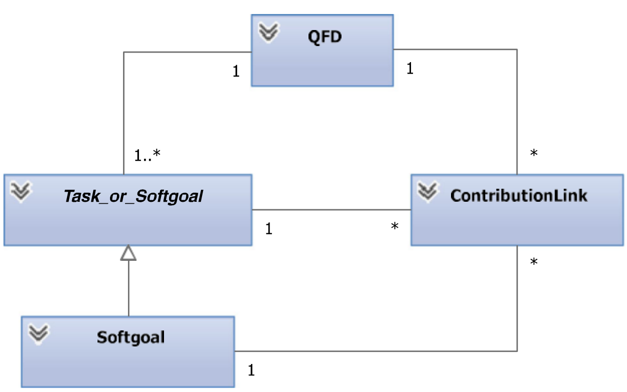


Fig. 13 QFD metamodel

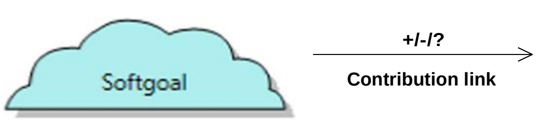


Fig. 14 Quality factors

Help: a partial positive contribution, yet not enough by itself to fulfill the softgoal.
Unknown: a contribution to a softgoal whose influence is unknown.
Some −: a negative contribution with unknown strength.
Hurt: a partial negative contribution, yet not enough by itself to deny the satisfaction of a softgoal.
Or: the parent is fulfilled if any of its children is fulfilled.
And: the parent is fulfilled if all its children are fulfilled.

3.6 Basic CSRML4BI Model Example

In this section, a basis CSRML4BI model is described as an example of a straightforward BI system (Fig. 15). Two kinds of stakeholders will participate in this system, i.e., *Actor 1* and *Actor 2* (Fig. 15a). There is only one *Actor 1* participating (cardinality 1), but one or more *Actors 2* may interact with the system (cardinality 1..*). All these actors will constitute the *GroupActor*, whose leader will be *Actor 1* (hand icon).

As expected, this model will represent a *Business Process*, consisting of one *Strategic Goal* (Fig. 15b). The *Strategic Goal* is decomposed into a *Collaborative Decision Goal* which, in turn, is decomposed into one *Information Goal*. The latter will be achieved thanks to the *System Main Task*. *Actor 1* will be involved in the accomplishment of the *Strategic Goal*, while the whole GroupActor will be involved in accomplishing the remaining goals.

It can be seen in Fig. 15c that there will be two roles, *Role 1* and *Role 2*, which will be played by *Actor 1* and *Actor 2* respectively, when certain guard conditions are accomplished. The previous *System Main Task* will consist of just one sub-task, namely *Task*, for which *Role 1* will be responsible.

The mentioned *Task* is to be specified in Fig. 15d and will be decomposed into one *Goal*, which will be satisfied by means of two *Information Requirements*, an individual and a collaborative one. Both Information Requirements will be decomposed into two resources, namely a *Measure* and a *Business Process Context* (see Sect. 3.4). In the case of the *Collaborative Information Requirement*, such resources will be shared. The *Information Requirement* will be performed by one (1) *Role 1*. However, in order to perform the *Collaborative Information Requirement*, one *Role 1* and one or more (1..*) *Roles 2* must participate. The *Awareness Resource* indicate that it is mandatory ([M]) for Role 1 to be aware of the *Presence* of others in order to participate in *Collaborative Information Requirement*.

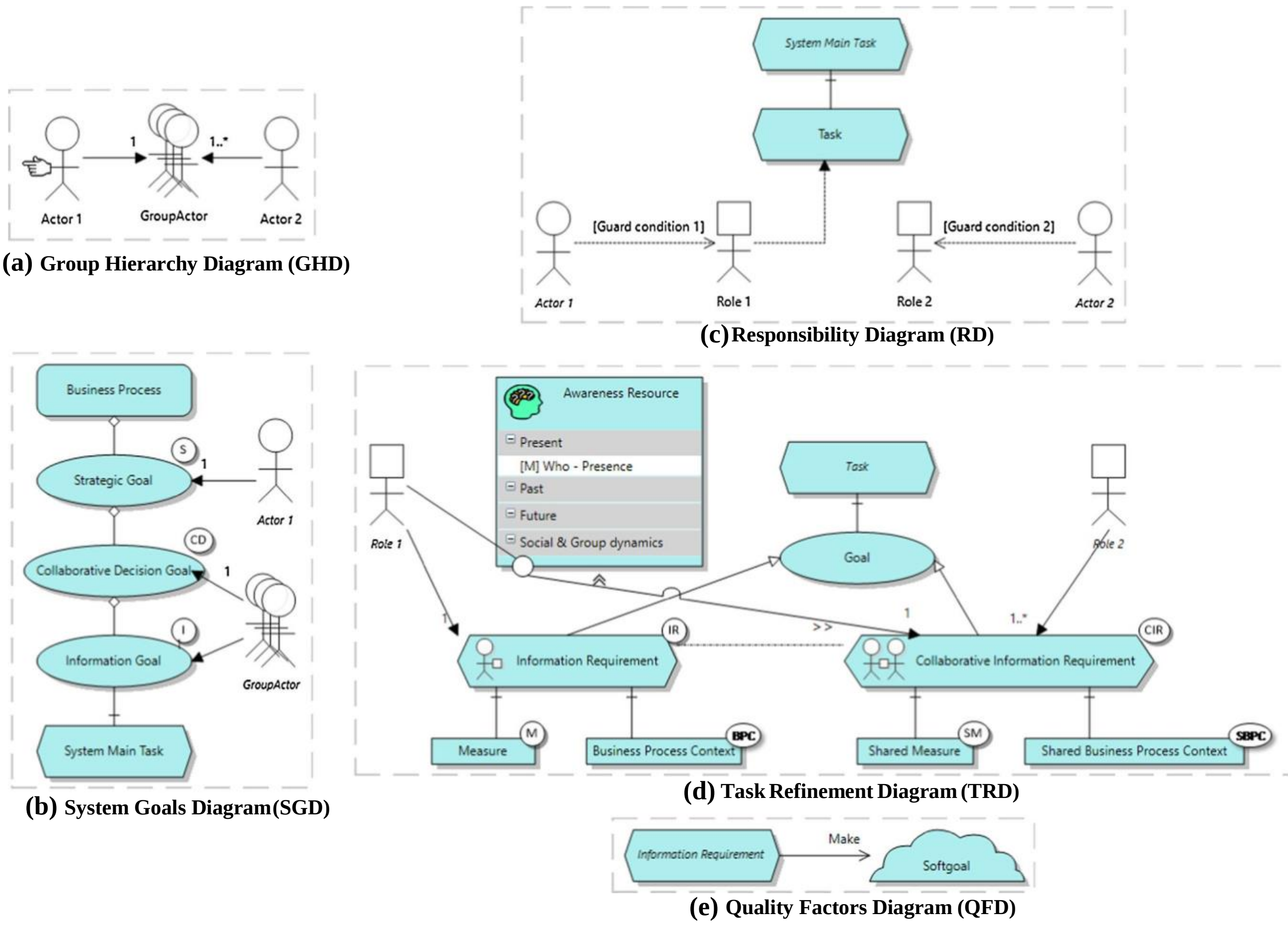


Fig. 15 Basic CSRML4BI model

There is a restriction between the two *Information Requirements*: *Information Requirement enables Collaborative Information Requirement.* Therefore, the former must be performed prior to the second.

Figure 15e specifies the sole quality factor present in this example, namely *Softgoal*. In this case, the previous *Information Requirement* will contribute positively to the satisfaction of the *Softgoal*.

3.7 CASE Support: CSRML4BI Tool

Since CSRML4BI is an evolution of CSRML for the BI domain, its CASE support has been developed by adapting the original CSRML CASE tool (Teruel et al. 2014) and extending it by the new BI features. Indeed, as the original tool, this new version as shown in Fig. 16 has also been integrated with Visual Studio to provide BI practitioners with facilities to specify and verify BI requirements models. This tool is available for the BI community through the Visual studio Marketplace (Teruel 2013).

4 Evaluation

To evaluate our proposal, a controlled experiment was carried out designed to compare CSRML4BI with *i**, the language it is based on. We compared both languages by using them to model two different systems and by then evaluating these models regarding their understandability, scalability, efficiency, and user satisfaction.

4.1 Experimental Context

The main goal of this experiment, defined by using Goal Question Metric (Basili et al. 1994) is defined as: *analyze i** and CSRML4BI *for the purpose of* evaluating the understandability, scalability, efficiency, and user satisfaction for both languages, *for* researchers *in the context of* BI practitioner and undergraduate students. To this aim, Table 1 presents the hypothesis that this experiment is trying to demonstrate.

It was decided to perform this experiment on experimental subjects from two different backgrounds. We first

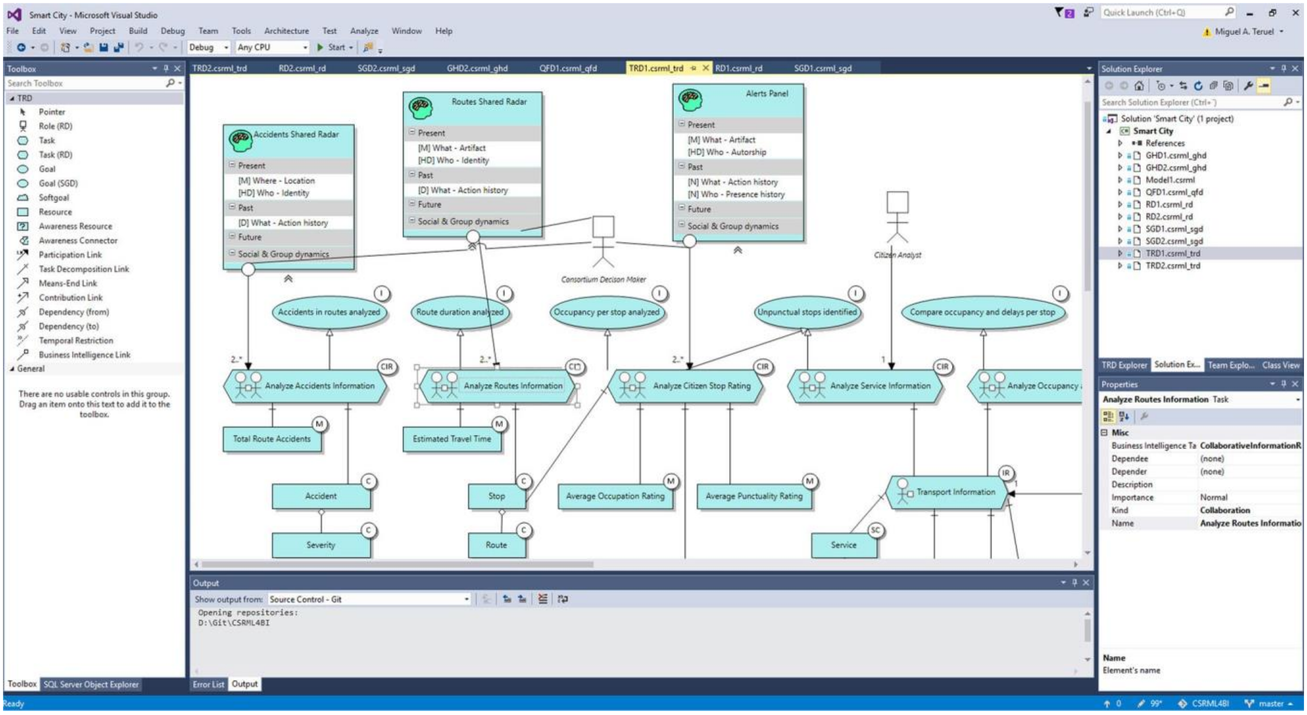


Fig. 16 CSRML4BI tool

Table 1 Main features of the experiment

Null hypothesis	H_{0A}: CSRML4BI and *i** have the same score for understandability of BI models. H_{1A}: $\neg H_{0A}$	
	H_{0B}: CSRML4BI and *i** have the same score for scalability of BI models. H_{1B}: $\neg H_{0B}$	
	H_{0C}: CSRML4BI and *i** have the same score for efficiency when analyzing BI models. H_{1C}: $\neg H_{0C}$	
	H_{0D}: CSRML4BI and *i** have the same score for user satisfaction when analyzing BI models. H_{1D}: $\neg H_{0D}$	
Dependent variables	Understandability score (UND), scalability score (SCA), efficiency score (EFF) and user satisfaction score (SAT)	
Independent variables	The language (CSRML4BI or *i**) used to specify the experimental models	
Location	Lucentia Lab (Sant Vicent del Raspeig, Spain)	University of Alicante (Sant Vicent del Raspeig, Spain)
Date	January 2018	February 2018
Subjects	9 Business Intelligence practitioners	62 Computer Science students

ran the experiment in a company specializing in creating BI solutions and chose participants with experience in understanding BI requirements models. The second experiment involved a large number of Computer Science students. The participants were required to have experience in requirements engineering as well as in elementary BI concepts, but not to have any previous experience of either CSRML4BI or *i** to avoid any bias.

4.2 Experimental Design

The experiment consisted of reading and understanding two different BI requirements models created with the two languages in question. To avoid the *learning effect*, a2 9 2 factorial design with confounded interaction (Winer et al. 1991) was used, as shown in Table 2.

It was decided to use a supply chain (domain 1) and a public transport system (domain 2) for the experimental model domains. The former specifies a supply chain for several supermarkets in which suppliers and managers must take collaborative decisions. The latter (partially) collects the requirements of a public transport system of the smart city depicted in ‘‘Appendix A’’. The experimental materials were thus requirements models of these two BI domains created with CSRML4BI and *i**. It should be noted that both the CSRML4BI and *i** models specify the same requirements, but were modeled with the languages being analyzed. However, the specification for CSRML4BI

Table 2 Experiment 2 9 2 factorial design with confounded interaction

		Domain	
		Supply chain (1)	Public transport (2)
Language	CSRML4BI	Group 1	Group 2
	*i**	Group 2	Group 1

Table 3 Statistics about the experiment

	Practitioners	Students
Number of participants	9	57
Average age	27.75	21.54
Percentage of female participants	22.22	14.04
Maximum elapsed time	0:35:00	0:43:00
Minimum elapsed time	0:21:00	0:17:00
Average elapsed time	0:26:20	0:27:33

was created by using the different diagrams that this language supports.

To analyze the understandability of both languages (UND) (ISO/IEC 9126 1991), we asked the participants 10 multiple-choice questions per model with 4 possibilities. UND was scored as the total number of correct answers. Regarding scalability (SCA), half of the questions (even numbers) required reading two or more diagrams (for CSRML4BI) in order to answer them correctly, and SCA was thus scored as the number of correct answers for the even questions.

For the measurement and evaluation of efficiency (EFF), the participants were asked to write down the current time before and after answering the 10 questions of each domain. This enabled us to compute the elapsed time for understanding each model. EFF was calculated as the number of correct answers per hour.

User satisfaction (SAT) was evaluated by asking the participants to answer different questions regarding several characteristics of the languages on a scale from 1 (nothing) to 5 (very) and were related to difficulty, understandability, readability, scalability, modifiability, traceability and expressivity. SAT was thus defined as the average score for each question. In the case of difficulty, the scale was defined from 1 (very hard) to 5 (very easy). For the sake of replicability, the models and questionnaires were published under a Creative Commons license (Teruel et al. 2018).

Finally, the experimental material given to the participants consisted of the following items:

- A double-sided A3 sheet of paper with the experimental models. Depending on the group (G1 or G2) the subjects belonged to, they were given a specific document (see Teruel et al. 2018).
- A questionnaire to fill in statistical data, answer the questions and express their personal opinion (see Teruel et al. 2018).
- Comprehensive documentation regarding both languages and their graphical notation (double-sided A4 sheet of paper per language) in case a participant had forgotten a concept.

The experimental task consisted of analyzing the provided paper models and then trying to answer the questionnaires.

Table 4 Questionnaire results per language and question

Participants	Group	Size	Language	Questions									
				1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	6 (%)	7 (%)	8 (%)	9 (%)	10 (%)
Practitioners	1	5	CSRML4BI	80	60	40	80	100	60	100	40	80	40
			*i**	0	20	100	20	60	80	20	0	20	60
	2	4	*i**	0	0	100	0	75	75	100	50	0	50
			CSRML4BI	75	0	75	100	75	75	100	50	75	25
Students	1	31	CSRML4BI	58	97	74	71	90	71	84	84	71	52
			*i**	3	3	45	19	42	81	16	13	0	84
	2	26	*i**	3	3	68	21	56	94	56	85	26	38
			CSRML4BI	94	12	53	41	85	59	53	59	59	29
Both	1	36	CSRML4BI	61	92	69	72	92	69	86	78	72	50
			*i**	3	6	53	19	44	81	17	11	3	81
	2	30	*i**	3	3	71	18	58	92	61	82	24	39
			CSRML4BI	92	11	55	47	84	61	58	58	61	29

Table 5 Experiment results per language

Subjects	Language	Results					Opinion							
		Q. odd	Q. even	Total	Time	Correct answers/h	Difficulty	Readability	Scalability	Understandability	Modifiability	Traceability	Expressivity	Total
Practitioners	CSRML4BI	4.00	2.65	6.65	0:14:35	27.36	3.18	3.63	3.70	3.27	3.23	3.53	3.90	3.49
	*i**	2.38	1.78	4.15	0:11:45	21.19	2.25	2.27	2.77	2.17	2.60	2.63	2.83	2.50
Students	CSRML4BI	3.61	2.87	6.48	0:14:00	27.77	2.77	3.46	3.25	2.85	3.25	3.27	3.60	3.21
	*i**	1.58	2.21	3.78	0:13:31	16.79	2.41	2.71	2.80	2.24	2.67	2.92	2.82	2.65
Any	CSRML4BI	3.65	2.83	6.48	0:14:04	27.66	2.82	3.48	3.30	2.89	3.23	3.30	3.63	3.24
	*i**	1.68	2.16	3.83	0:13:19	17.27	2.39	2.65	2.79	2.22	2.67	2.88	2.83	2.63

4.3 Running the Experiment

The experiment was carried out in two different locations, first in the meeting room of a BI company with practitioners as the experimental subjects, then in a university classroom with undergraduates, whose experimental results are comparable to those obtained by professionals, according to Höst et al. (2000). In both places, the experiment started with an introductory session, presenting both languages and the goal and procedure of the experiment. These sessions took around 30 min each. After this short introduction, the participants were given the experimental material.

To facilitate the participation in this experiment, both the introduction and the experimental material were translated into Spanish. Since there was no CASE tool able to model both CSRML4BI and *i** models, all the material used was provided on paper. There were no dropouts during the experiment.

Table 3 summarizes the statistical data gathered, as well as the time participants took to complete the experiment.

4.4 Results

After recording the participants' paper questionnaires, we obtained the results shown in Tables 4 and 5. CSRML4BI surpassed *i** regarding the four different dependent variables evaluated, regardless of the group of participants. In the following subsection, these dependent variables are analyzed in detail.

4.4.1 Understandability

As can be seen in Fig. 17, CSRML4BI obtained better results than *i** for understandability (UND), regardless of participant groups. These results were computed as the average score for all the questionnaire questions. Both practitioners and students achieved proportionally similar results. However, practitioners surpassed students in understanding BI requirements models (6.65 and 4.15 vs. 6.48 and 3.78).

In order to accept or reject the null hypothesis H_{0A}, a 2-Sample t Test was performed (Fig. 18) with an alpha of 0.05. Thanks to this test, we could conclude that the means for UND differ at the 0.05 level of significance, with a *p* value less than 0.001. With a 95% confidence level, the true difference was between 1.9634 and 3.2528, so that we rejected the null hypothesis H_{0A}, meaning that CSRML4BI does not have the same score for understandability of the BI models.

In the results of Question No. 5, directly related to collaboration, CSRML4BI obtained 92% for model 1 and 84% for model 2, while *i** received 44% and 58%

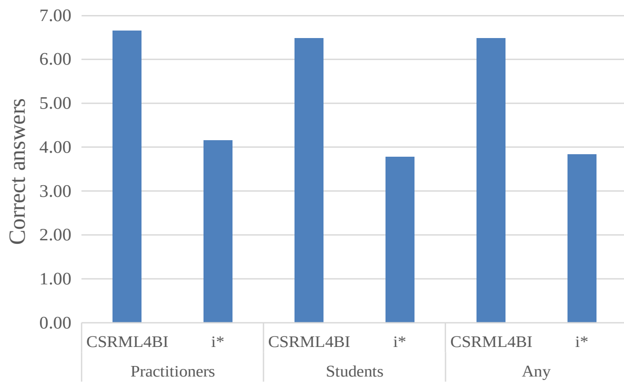


Fig. 17 Understandability results

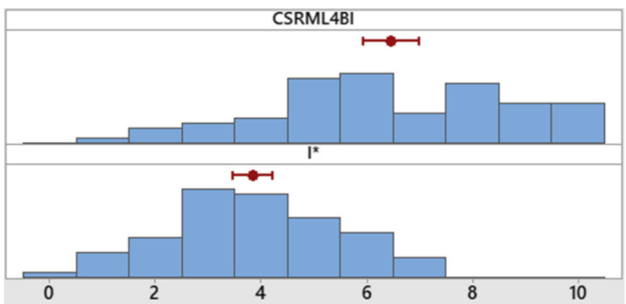


Fig. 18 Distribution of data for understandability (correct answers)

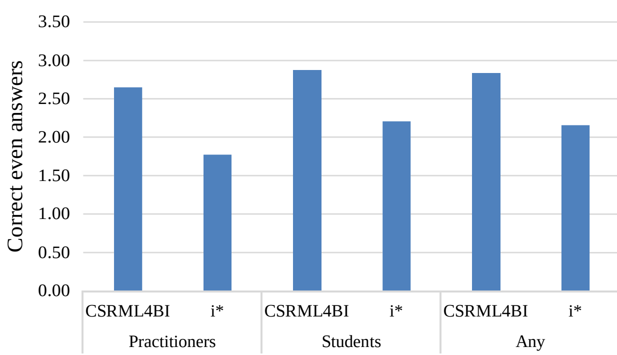


Fig. 19 Scalability results

respectively. These results indicate that CSRML4BI is much more understandable than *i** when dealing with collaboration among users, this being one of the cornerstones of our proposal.

4.4.2 Scalability

The scalability score was computed as the average number of correct answers for the questions which required

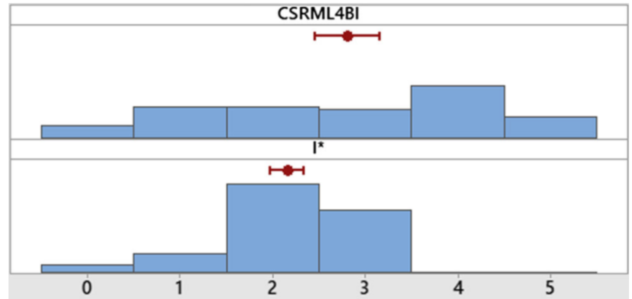


Fig. 20 Distribution of data for scalability (correct even answers)

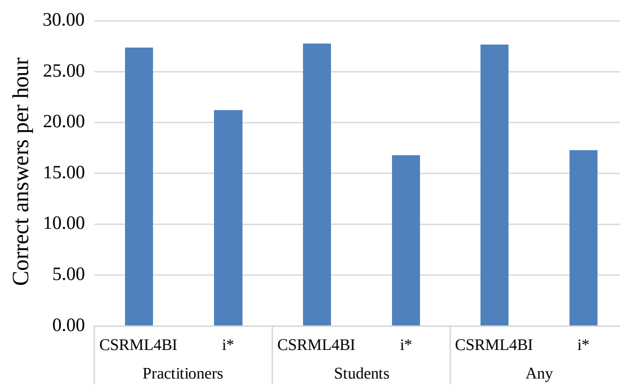


Fig. 21 Efficiency results

consulting several diagrams in the case of CSRML4BI. As these were the even questions, (see Teruel et al. 2018), each subject had to assess them in a scale from 0 to 5. Similarly to UND, the results were better for CSRML4BI, regardless of the type of participant (Fig. 19), although in this case the difference was not so high.

To assess that difference, a *t* test was performed again (Fig. 20). Here we concluded once more that the means for SCA differ at the 0.05 level of significance (*p* value = 0.001). However, the obtained confidence interval was lower in this case, being (0.25843, 1.0389) at a 95% confidence level. We thus rejected the null hypothesis H_{0B}, so CSRML4BI and *i** do not have the same score for scalability of BI models.

4.4.3 Efficiency

Efficiency (EFF) was measured as the number of correct answers per hour. For this variable, the 10 questions were taken into account. Once again, CSRML4BI obtained a better score in both types of participant (Fig. 21), although there was a difference in the means of 6.17 correct answers per hour for the practitioners and 10.98 for the students.

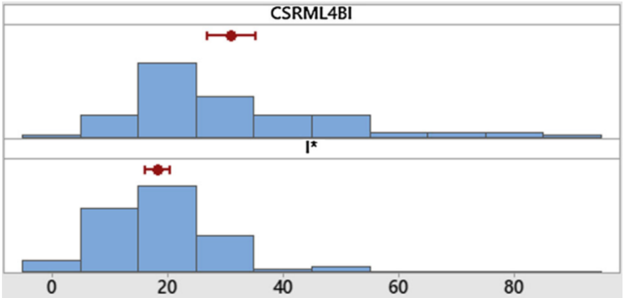


Fig. 22 Distribution of data for efficiency (correct answers per hour)

Therefore, the use of CSRML4BI instead of *i** affected the efficiency of students more than practitioners.

Once again, a t-Test was performed regarding the null hypothesis H_{0C} (Fig. 22). This null hypothesis was also rejected, since the means differed at the 0.05 level of significance, with a p value $<$ 0.001 and a 95% confidence interval of (8.0707, 17.333). Hence, CSRML4BI and *i** do not have the same score for efficiency when analyzing BI models.

4.4.4 User Satisfaction

User satisfaction (SAT) was measured as the average score of the personal opinion questions (see Teruel et al. 2018). For this variable, CSRML4BI obtained a better score than *i** for individual questions (difficulty, understandability, readability, scalability, modifiability, traceability and expressivity), as shown in Fig. 23. The total (average of these 7 metrics) was also better, as would later be confirmed by a *t* test.

The *t* test also rejected the null hypothesis H_{0D}, since the means differ at the 0.05 level of significance, with a p value $<$ 0.001, and a 95% confidence interval of (0.26242, 0.74085) (Fig. 24). Because of this result, H_{0D} is rejected, so CSRML4BI and *i** do not have the same score for user satisfaction when analyzing BI models.

Two of the questions concerning personal opinions can also be used as a subjective measurement for UND and SCA variables [see Teruel et al. (2018), it is understandable by a non-expert and it is scalable]. These results on personal opinion coincide with the objective ones (UND and SCA), as can be seen in Table 6. The ratio between both subjective and objective results is closer to 1 for understandability than scalability.

To sum up, in view of the results for the four dependent variables, it can be said that CSRML4BI is more suitable for modeling BI requirements than *i**, regardless of the user's background (practitioner or student).

4.5 Threats to the Validity

As suggested by Wohlin et al. (2012), in the following the most relevant threats to the validity of the controlled experiment described here are analyzed.

Internal validity is related to the influences on the independent variable (Wohlin et al. 2012). The different subjects that participated in the experiment were not informed previously, avoiding social threats. A 2 × 2 factorial design was applied, so that in each group the language and the system were changed after a break between the two sessions. The subjects were randomly assigned within the groups to cancel out both learning and fatigue effects.

According to Wohlin et al. (2012), external validity threats are related to the generalization of the experiment. The experimental subjects in the experiment had a

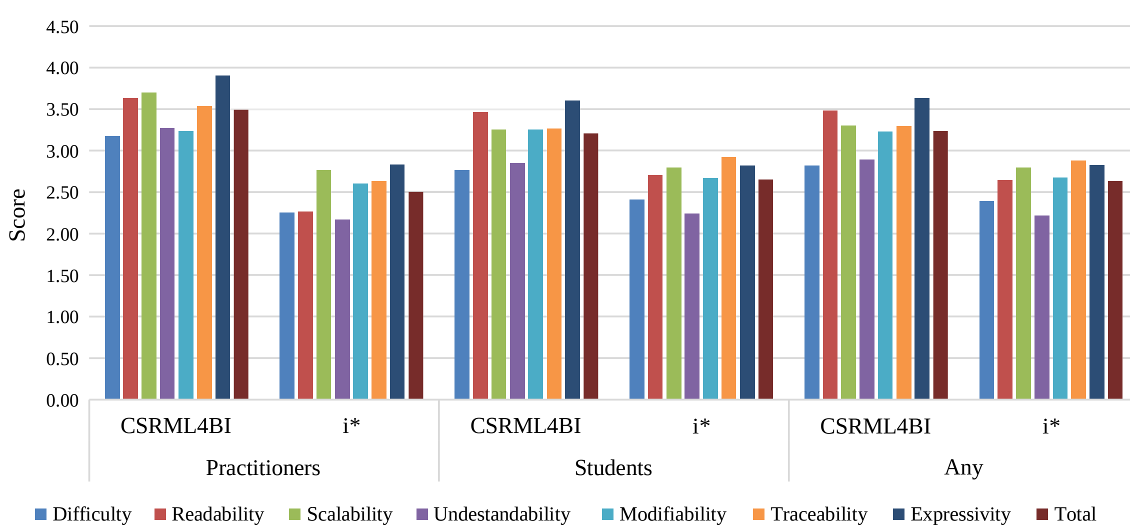


Fig. 23 User satisfaction results

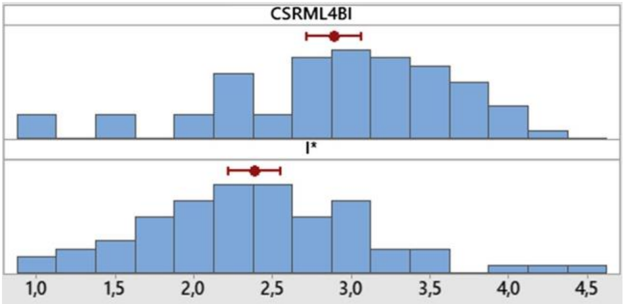


Fig. 24 Distribution of data for user's satisfaction (score)

sufficient maturity level because the tasks to be carried out were not highly demanding in terms of industrial experience (Hö st et al. 2000). However, it should also be noted that the practitioners who participated in the experiment had similar results for the experimental tasks. The models used for the evaluation were a partial description that could have been used to describe a real system in an industrial setting.

The method applied to evaluate the outcome of the experimental task may threaten the Construct validity (Wohlin et al. 2012) of the experiment. In order to avoid this threat, a questionnaire was used to evaluate its understandability. Prior to conducting the experiment, external experts tried to complete the questionnaires after analyzing the models, and we then refined the models and questions until they reached an understandability score of 100% for each model, thus reducing the chance of bias towards one of the languages.

Conclusion validity threats are related to the statistical relationship between the independent and dependent variables (Wohlin et al. 2012). The statistical power can be considered high, since 66 subjects participated in the experiment, being enough according to the central limit theory. We also avoided the ''fishing for the result'' effect as we focused the analysis on which language, *i** or CSRML4BI, provided the best support for the specification of BI requirements. Finally, the experiment was not balanced, that is, the number of participants per group were different as shown in Table 4, the first group being bigger than the second. The authors of this paper did not monitor the running of the experiment to avoid introducing any bias.

5 Conclusions and Future Work

Collaborative BI is commonly practiced in companies as it helps decision makers to make the most of the available information as well as to analyze the problem from other points of view. However, this approach is barely supported by currently available tools. Recent proposals focus on the improvement of the technical side of the development of these systems. However, they may significantly benefit from a requirements modeling technique that enables designers to specify the collaborative system requirements. These systems could really provide the expected and needed functionality as well as consider important aspects of the CSCW community, such as awareness.

In this work, we present CSRML4BI, a goal-oriented and i*-based framework for collaborative BI, that offers expressive facilities to identify and model (1) the decision-making tasks that require collaboration among the participants, (2) the participants involved in collaborative decision making, and (3) the information required and shared among them. Of the new elements in CSRML4BI, it is important to highlight the facilities for specifying the business goals to be defined, the collaborative information requirement that helps stakeholders analyze the goals of the system from different perspectives, as well as the resources, especially those related to measures and shared contexts, which may help decision makers to make decisions based on quantitative data.

In order to guide the process of applying CSRML4BI, its core elements were applied to specify the Smart City Dashboard (see ''Appendix A''). This specification was carried out using the different diagrams that CSRML4BI recommends, conducting an iterative refinement process from the actors and goals of the system to the tasks to be supported. Special attention was paid to the collaborative

Table 6 Comparison between objective and subjective results for understandability and scalability

	Language	UND			SCA		
		Objective[a]	Subjective	Ratio	Objective	Subjective	Ratio
Practitioners	CSRML4BI	6.65	3.27	1.02	2.65	3.70	0.72
	*i**	4.15	2.17	0.96	1.78	2.77	0.64
Students	CSRML4BI	6.48	2.85	1.14	2.87	3.25	0.88
	*i**	3.78	2.24	0.84	2.21	2.80	0.79
Both	CSRML4BI	6.48	2.89	1.12	2.83	3.30	0.86
	*i**	3.83	2.22	0.86	2.16	2.79	0.77

[a]Scale from 0 to 10

side of the specification, one of the main strengths of CSRML4BI.

To facilitate the specification of a collaborative BI system, a CASE tool (Teruel 2017) was developed and made available for BI practitioners. This tool consists of an extension of an already existing tool (Teruel et al. 2014), which was modified to support the new CSRML4BI. The new tool, which is currently available for free, has been fully integrated with Visual Studio to obtain a complete IDE for the development of BI collaborative applications. Thus, BI designers could benefit from the advantages this tool provides, such as improved correctness of the models, thanks to its automatic validation. Traceability of model diagrams is also improved, since it will manage the links between diagrams and elements.

A controlled experiment was performed to compare CSRML4BI with *i** for modeling BI requirements. Four different characteristics were taken into account (understandability, scalability, efficiency, and user satisfaction), and two different types of experimental subjects were used, namely BI practitioners and Computer Science undergraduate students. CSRML4BI obtained a better score than *i** for the four variables in both types of participants. Understandability and scalability were assessed in an objective (number of correct answers and correct answers per hour) and subjective manner (score for personal opinion). Once again, CSRML4BI obtained a better score for both the objective and the subjective measurement of understandability and scalability, regardless of the subjects' background.

Our future work will consist of several lines of research. It is planned to evaluate which goal reasoning techniques, such as that presented by Giorgini et al. (2008), may be used to exploit the different alternatives specified by CSRML4BI. As part of our on-going work, we are analyzing how to exploit the collaborative requirements modeled in CSRML4BI to automatically provide collaborative support within BI platforms. Finally, we will develop a series of guidelines and video tutorials to promote the language's use among the BI community. By following these guidelines, a BI practitioner will be able to use CSRML4BI for modeling a BI system by following a step-by-step procedure that will lead to the identification of BI goals, actors, collaborative tasks and so on. We are also considering developing a model-driven tool that generates a scaffolding code to build the final application, taking a complete specification of a collaborative BI system as its input.

In a different vein, an additional experiment will be performed to evaluate the scalability of CSRML4BI from a new point of view. Case studies for varying system sizes will be considered, which would enable us to assess whether our proposal's scalability depends on the size of the BI system.

References

Asur S, Huberman BA (2010) Predicting the future with social media. In: 2010 IEEE/WIC/ACM international conference on web intelligence and intelligent agent technology. IEEE, Toronto, pp 492–499

Basili VR, Caldiera G, Rombach HD (1994) The goal question metric approach. In: Marciniak J (ed) Encyclopedia of software engineering. Wiley, New York, pp 528–532

Berthold H, Rösch P, Zöller S et al (2010) An architecture for ad-hoc and collaborative business intelligence. In: 1st International workshop on data semantics (DataSem'10). ACM Press, Lausanne, pp 13:1–13:6

Dalpiaz F, Franch X, Horkoff J (2016) iStar 2.0 language guide. Cornell University. http://arxiv.org/abs/1605.07767

Dayal U, Vennelakanti R, Sharma R et al (2008) Collaborative business intelligence: enabling collaborative decision making in enterprises. In: Meersman R, Tari Z (eds) On the move to meaningful internet systems: OTM 2008. Springer, Berlin, pp 8–25

de Moor A (1999) Empowering communities: a method for the legitimate user-driven specification of network information systems. Tilburg University, Tilburg

Devlin B (2012) Collaborative business intelligence: socializing team-based decision making. Bus Intell J 17:9–17

Embley DW, Liddle SW (2013) Big data – conceptual modeling to the rescue. In: Ng W, Storey VC, Trujillo JC (eds) ER 2013: conceptual modeling. Springer, Berlin, pp 1–8

Figueroa-Martinez J, López-Jaquero V, Gutiérrez Vela FL, González P (2013) Enriching UsiXML language to support awareness requirements. Sci Comput Program 78:2259–2267. https://doi.org/10.1016/j.scico.2012.09.020

Giorgini P, Mylopoulos J, Nicchiarelli E, Sebastiani R (2003) Formal reasoning techniques for goal models. J Data Semant I 2800(2003):1–20

Giorgini P, Mylopoulos J, Sebastiani R (2005) Goal-oriented requirements analysis and reasoning in the tropos methodology. Eng Appl Artif Intell 18:159–171

Giorgini P, Rizzi S, Garzetti M (2008) GRAnD: a goal-oriented approach to requirement analysis in data warehouses. Decis Support Syst 45:4–21. https://doi.org/10.1016/j.dss.2006.12.001

Golfarelli M, Mandreoli F, Penzo W et al (2012) BIN: business intelligence networks. In: Zorrilla ME, Mazón J-N, Ferrández Ó et al (eds) Business intelligence applications and the web: models, systems and technologies. IGI Global, Hershey, pp 244–265

Gross T (2013) Supporting effortless coordination: 25 years of awareness research. Comput Support Coop Work 22:425–474. https://doi.org/10.1007/s10606-013-9190-x

Gutwin C, Greenberg S (2002) A descriptive framework of workspace awareness for real-time groupware. Comput Support Coop Work 11:411–446. https://doi.org/10.1023/A:1021271517844

Horkoff J, Yu E (2010) Finding solutions in goal models: an interactive backward reasoning approach. In: International conference on conceptual modeling. Springer, Aachen, Germany, pp 59–75

Horkoff J, Yu ES-K (2012) Comparison and evaluation of goal-oriented satisfaction analysis techniques. Requir Eng 18:199–222. https://doi.org/10.1007/s00766-011-0143-y

Höst M, Regnell B, Wohlin C (2000) Using students as subjects – a comparative study of students and professionals in lead-time impact assessment. Empir Softw Eng 5:201–214. https://doi.org/10.1023/A:1026586415054

ISO/IEC 9126 (1991) Software engineering – product quality. ISO/IEC. https://www.iso.org/standard/22749.html. Accessed 27 July 2018

Kaufmann J, Chamoni P (2014) Structuring collaborative business intelligence: a literature review. In: 2014 47th Hawaii international conference on system sciences. IEEE, Waikoloa, pp 3738–3747

Kelly J, Jones P, Barta F et al (2004) Successful transport decision-making: a project management and stakeholder engagement handbook. European Commission, Brussels

Lakomaa E, Kallberg J (2013) Open data as a foundation for innovation: the enabling effect of free public sector information for entrepreneurs. IEEE Access 1:558–563. https://doi.org/10.1109/ACCESS.2013.2279164

Limbourg Q, Vanderdonckt J, Michotte B et al (2004) USIXML: a language supporting multi-path development of user interfaces. In: Bastide R, Palanque P, Roth J (eds) Engineering human computer interaction and interactive systems. Springer, Berlin, pp 200–220

Lindman J, Rossi M, Tuunainen VK (2013) Open data services: research agenda. In: 2013 46th Hawaii international conference on system sciences. IEEE, Wailea, pp 1239–1246

Liu L, Daniels H (2012) Towards a value model for collaborative, business intelligence-supported risk assessment. In: 6th International workshop on value modeling and business ontology (VMBO'12). Vienna, pp 1–5

Martínez-Carreras MA, Muñoz A, Botía J (2013) Building and evaluating context-aware collaborative working environments. Inf Sci (NY) 235:224–241. https://doi.org/10.1016/j.ins.2013.02.009

Maté A, Trujillo J, Franch X (2011) A modularization proposal for goal-oriented: analysis of data warehouses using I-star. In: 30th International conference on conceptual modeling (ER'11), pp 421–428

Mazón J-N, Pardillo J, Trujillo J (2007) A model-driven goal-oriented requirement engineering approach for data warehouses. In: Hainaut J-L, Rundensteiner EA, Kirchberg M et al (eds) Advances in conceptual modeling - foundations and applications. Springer, Berlin, pp 255–264

Mettler T, Raber D (2011) Developing a collaborative business intelligence system for improving delivery reliability in business networks. In: 2011 17th International conference on concurrent enterprising, Aachen, pp 1–7

Moody DL (2009) The ''Physics'' of notations: toward a scientific basis for constructing visual notations in software engineering. IEEE Trans Softw Eng 35:756–779. https://doi.org/10.1109/TSE.2009.67

Oh O, Agrawal M, Rao HR (2013) Community intelligence and social media services: a rumor theoretic analysis of tweets during social crises. MIS Q 37:407–426

Pohl K (2010) Requirements engineering: fundamentals, principles, and techniques. Springer, Berlin

Pressman RS (2009) Software engineering: a practitioners approach, 7th edn. McGraw-Hill Science/Engineering/Math, New York

Rizzi S (2012) Collaborative business intelligence. In: Aufaure M-A, Zimányi E (eds) Business intelligence. Springer, Berlin, pp 186–205

Schmidt K, Bannon L (1992) Taking CSCW seriously. Comput Support Coop Work 1:7–40. https://doi.org/10.1007/BF00752449

Teruel MA (2013) CSRML Tool 2013. https://marketplace.visualstudio.com/items?itemName=MiguelATeruel.CSRMLTool2013. Accessed 23 June 2017

Teruel MA (2017) CSRML4BI Tool. http://bit.ly/2nrfqOC. Accessed 23 June 2017

Teruel MA, Navarro E, López-Jaquero V et al (2011a) CSRML: a goal-oriented approach to model requirements for collaborative systems. In: Jeusfeld M, Delcambre L, Ling T-W (eds) Conceptual modeling – ER 2011. Springer, Berlin, pp 33–46

Teruel MA, Navarro E, López-Jaquero V et al (2011b) A comparative of goal-oriented approaches to modelling requirements for collaborative systems. In: 6th International conference on evaluation of novel software approaches to software engineering (ENASE'11). SciTePress, Beijing, pp 131–142

Teruel MA, Navarro E, López-Jaquero V et al (2012) Analyzing the understandability of requirements engineering languages for CSCW systems: a family of experiments. Inf Softw Technol 54:1215–1228. https://doi.org/10.1016/j.infsof.2012.06.001

Teruel MA, Navarro E, López-Jaquero V et al (2014) A CSCW requirements engineering CASE tool: development and usability evaluation. Inf Softw Technol 56:922–949. https://doi.org/10.1016/j.infsof.2014.02.009

Teruel MA, Navarro E, González P et al (2016) Applying thematic analysis to define an awareness interpretation for collaborative computer games. Inf Softw Technol 74:17–44. https://doi.org/10.1016/j.infsof.2016.01.009

Teruel MA, Maté A, Navarro E et al (2018) The new era of business intelligence applications: building from a collaborative point of view – experimental material. Technical report no. DIAB-18-04-2. Computing systems department, University of Castilla–La Mancha

Vitali M, Pernici B, O'Reilly U-M (2015) Learning a goal-oriented model for energy efficient adaptive applications in data centers. Inf Sci (NY) 319:152–170. https://doi.org/10.1016/j.ins.2015.01.023

Winer BJ, Brown DR, Michels KM (1991) Statistical principles in experimental design, 3rd edn. McGraw-Hill Humanities/Social Sciences/Languages, New York

Wohlin C, Runeson P, Höst M et al (2012) Experimentation in software engineering. Springer, Berlin

Yu ESK (1997) Towards modelling and reasoning support for early-phase requirements engineering. In: 3rd IEEE international symposium on requirements engineering (ISRE'97). IEEE Computer Society Press, Annapolis, pp 226–235

Zhu M-X, Luo X-X, Chen X-H, Wu DD (2012) A non-functional requirements tradeoff model in trustworthy software. Inf Sci (NY) 191:61–75. https://doi.org/10.1016/j.ins.2011.07.046

Zikopoulos PC, Eaton C, de Roos D et al (2011) Understanding big data: analytics for enterprise class hadoop and streaming data. McGraw-Hill Osborne, New York