Natural Language *Why-Question* in Business Intelligence Applications: Model and Recommendation approach

Meriem Amel GUESSOUM[1*†], Rahma DJIROUN[1*†], Kamel BOUKHALFA[1*†] and Elhadj BENKHELIFA[2*†]

[1*]Laboratory of Information System LSI, USTHB, Algiers,Algeria.
[2]Cloud Computing and Application Research Lab, Staffordshire University, UK.

*Corresponding author(s). E-mail(s): mguessoum@usthb.dz; rdjiroun@usthb.dz; kboukhalfa@usthb.com; e.benkhelifa@staffs.ac.uk;
†These authors contributed equally to this work.

Abstract

Business Intelligence is the key technology for users to effectively extract valuable information from oceans of data for decision- making. Data warehouses and on-line analytical processing systems have therefore been developed to contribute effectively to the decision-making process. To extract information that is useful to decision-making, decision-makers express their needs in natural language. Such requirements may be formulated in natural language interfaces in free syntax, avoiding unfamiliar language (SQL, MDX). Natural Language queries can stand for WH-questions *("What, Who, Where, Why, etc.")* or a set of Keywords. In this paper, we emphasize on the *"Why-Question"*. This type of question provides answers that help in the diagnosis analysis of the data Warehouse. To deal with a *Why-Question*, we propose a model that mainly captures the components that reflect the multidimensional aspect of the Data Warehouse. When a decision-maker formulates his *Why-Question* in natural language, he uses his own terms. This decisional need can be not precise because the decision-maker is not always aware of the Data Warehouse's lexicon as well as the *Why-Question's* model. Consequently, the decision-maker must reformulate his initial question. Otherwise, the *Why-Question's* answering process will not be triggered. This situation is not obvious for a decision-maker, especially when the reformulation of the question becomes iterative. To handle these issues, we lean towards a *Why-Question's* recommendation approach based on both the Data Warehouse's content and the decision maker's requirement. This proposal aims to recommend to the decision-maker a set of natural language *Why-Questions* instead of rephrasing his initial question. To guide the recommendation process, we rely on a grammar that formalizes the *Why-Question's* model. To validate our approach, a tool called *"WQ-Recommender"* is developed. An experimental study is presented to evaluate the relevance of the proposal.

Keywords: Business Intelligence, Data Warehouse, Why-Question, Recommendation, Grammar

1 Introduction

When the decision maker is confronted with choices requiring thorough analysis of data, the decision-making process becomes complex. In this perspective, Business Intelligence (BI) systems and tools have been developed to ease the decision-making process. BI is the key technology for users to efficiently extract useful information from oceans of data. Data Warehouses (DW) and the Online Analytical Processing (OLAP) Systems are effective contributors to the decision-making process.

In the context of DW, the decision maker can't always easily query data without a minimum mastery of formal languages (SQL, MDX). Therefore, soliciting the *IT-Designer* becomes obvious in order to extract Business information. To minimize the *IT-Designer's* intervention as much as possible, Question Answering (Q/A) systems provided with Natural Language (NL) interfaces have been set up. Such systems handle decision makers' requirements expressed as NL questions in free syntax without any technical prerequisite as in[23, 31, 38, 41, 42]. Indeed, nowadays, BI technologies are moving towards self-service solutions (modern BI) [18]. These solutions are in the sense of Question/Answering systems as in [7, 40]. Such applications serve to assist the analytic conversation. They allow decision-makers to interact intuitively with the DW by asking questions as they come to mind and without in-depth knowledge of the query tool or formal languages (SQL, MDX). However, researchers move recently towards integrating chatbots applications based on a NL Dialogue flow [45] in order to interact with dashboards. These applications enable decision-makers to ask NL queries and receive instant responses instead of navigating in the dashboard. This approach has good properties such as speed, accessibility, compatibility, and interactivity over traditional BI dashboard [45].

Traditional Q/A systems provide answers from unstructured data (documents) [25]. The BI context is quite different because it is about extracting answers from structured data with multidimensional representation [25]. In such context, the Q/A systems procure decision-makers with an intuitive way to interact with DWs. Thus, decision-makers can express their requirements as NL questions. In essence, NL questions can be categorized as WH-questions (What, Where, etc.), keywords like questions, etc. In literature, the questions those has attracted the researcher's attention are the What-Questions [24, 31, 41] and keyword-like-Questions [23]. Often, these questions do not fully meet the needs of the decision-maker. Indeed, usually, decision-makers seek to know the origin of phenomena observed on a certain activity (decrease in sales, increase in recourse, etc.). In this perspective, the decision-making need can take the form of a *Why-Question* such as *"Why has the number of accidents increased in 2021? "Why has the internet sales amount decreased?"*. This question type is interesting, allowing decision-makers to understand some decision-making indicators such as the cause or origin of a trend, causes of customers' behavior [16]. Indeed, a *Why-Question* allows decision-makers to perform diagnostic analysis on the data of the Warehouse.

In literature, most researchers report that addressing a NL *Why-Question* is a complex task and the expected answers require particular methods and deep analysis to provide them [23].

The *Why-Questions* have been widely addressed in the Information Retrieval (IR) field. Indeed, several approaches have been proposed in order to develop *Why-Questions* answering systems as in [3, 33–36]. However, these approaches are not suitable in the BI context. Indeed, these approaches have been not designed to address a NL *Why-Question* asked in the BI context. To deal with this question, it is mandatory to take into account the multidimensional concepts characterizing a DW (facts, measures, dimensions, hierarchies, etc.). These concepts are crucial in a decision-making system.

To address a NL *Why-Question* emitted in BI context, we have proposed in [16] an approach that aims at providing decision-makers with answers that allow them to detect factors that influence a phenomenon, for effective decision support. Our approach emphasizes on both the decision maker's requirement and the DW (concepts and content). The *Why-Question's* answering process is not limited to interpreting a NL question into SQL or MDX queries. It is based on a mathematical model that performs a deep analysis on the Warehouse's data. Since the answering process is closely related to the decision maker's requirement, we have proposed in [16] a *Why-Question's* model that captures the necessary components and constraints (a *Why-Question* must comport a measure, trends, temporal or not temporal dimensions) upon which our approach is built. In our approach [16], the decision-maker formulates freely, his *Why-Question* through using his own terms in NL. However, this scenario of querying a DW engenders some issues:

(1) - The decision-makers are not always aware of the DW schema (concepts);
(2) - When the *Why-Question* doesn't conform to the model that defines it, the approach [16] does not generate answers. For example: *"Why didn't the company evolve? In this question no measure that belongs to a DW is expressed so the answering process can't be triggered;*
(3) - In a such situation, the decision maker must reformulate his question. Unfortunately, this operation can become iterative and therefore the decision-maker finds himself in a closed circle;
(4)- Automatic reformulation is not always possible because a Why-Question is qualified as subjective, especially when the decision-maker's requirement is not precise;
(5) - This scenario of querying a DW proves binding for the decision-maker. It can annoy the decision maker, which is incompatible with the principle of the design of NL interfaces;
High complexity is considered to be a major constraint of BI environments [48]. While searching for an answer to a business question, the end-user (decision-makers) finds it difficult to navigate large data repositories [20] and DWs. It is important to know that most of the times the user doesn't know the right business question to ask [26]. To solve these complexities, it is important to integrate a recommendation mechanism into a BI system [20]. A recommendation process is necessary to meet the needs of the decision-makers need. Thus, it is more interesting to suggest to the decision-maker a set of NL Why-Questions instead of rephrasing his initial question. Hence, the Why-Question's answering process will be performed with respect to a question that well captures the decision-maker's needs and consequently return him the most appropriate answers for effective decision-making.

In recent decades, several recommendation mechanisms have been integrated into BI systems in order to enhance their functionality and to increase the benefits that decision-makers can derive from querying DWs as in [2, 11, 14, 15, 21, 22, 32, 43] and to improve the ergonomics of BI tools (dashboards) as in [20]. Unfortunately, most of these approaches focused only on recommending formal queries (SQL, MDX), in order to query DWs, from formal ones as in [2, 14, 15, 21, 22, 32, 43] and from a set of keywords as in [11]. However, authors in [20], propose to integrate a feedback and recommendation mechanism (FRM) into BI tools. This mechanism helps the user by generating textual and/or graphical visual cues, and thus leading the user to consider the use of certain data subsets and/or analysis forms [20].

To the best of our knowledge, no work has proposed an approach for the recommendation of NL questions in the BI context. In contrast, question recommendation has been intensively researched in Web Question Answering community (CQA) as in [1, 13, 17, 19, 27–29, 39, 44, 50, 51]. These recommendation approaches proposed in CQA are performed on the basis of models that only evaluate similarities between the user's question and the data sources (question's collection) such as the language model, the user's model and the topic models. Unfortunately, these models prove insufficient when it comes to dealing with a question asked in BI context. Indeed, the most appropriate model to use must consider the multidimensional aspect of a DW that reveals the concepts of DW as well as the relations linking these concepts (measures, dimension, dimension's hierarchy level and dimension's attribute). Therefore, we can't fully adopt the IR recommendation models in the context of our work, i.e.the recommendation of decisional NL *Why-Questions.*

Motivated by the lacks discussed above, we propose in this paper a recommendation approach based on both the content of the DW as well as the needs of the decision maker. This approach aims at easing the querying of the DW by generating a set of NL *Wh-Questions* from a question initially introduced by the decision maker. This question may represent a not precise Business need. Therefore, recommending to the decision maker questions closest to his requirement may procure him more clarity on the ideas that he has in mind. Thereafter, the decision maker will choose the most adequate *Why-Question* that avoids him the reformulation of his input question. Thus, the recommendation process grantee that the triggering of the answering process will generate answers with respect to the *Why-Question* chosen by the decision maker.
To determine the information that characterizes the *Why-Question* introduced by the decision-maker, an analysis process is mandatory. In our approach, this process is performed mainly on the

basis of grammar that we propose. This grammar is a pattern that aims at formalizing the model that specifies the desired content of a *Why-Question*. Indeed, our grammar captures all the restrictions defined in the *Why-Question's* model [16]. To build this grammar, we adopt first the linguistic patterns proposed by *"BARGUI and al"* in [4, 5] and then we extend them with respect to our *Why-Question's* model. This grammar can be reusable and extensible according to what is defined in the *Why-Question's* model.
Our proposed grammar has dual roles in our approach, the first concerns the *Why-Question's* analysis process. The second role is that the grammar guides the recommendation process when the *Why-Question* doesn't conform to its model [16] as illustrated in the figure 1

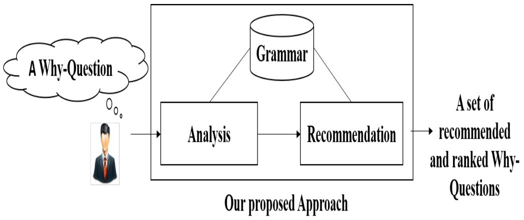

Fig. 1 General schema of our proposed approach.

The structure of this paper is as follows: section 2 captures works related to our research one. In section 3, we present the proposed grammar and remind about the decisional NL *Why-Question's* model. Section 4 describes our proposed *Why-Question* recommendation approach. An experimental study is shown in section 5. In section 6, we conclude the paper and draw some future lines of research.

2 Related Works

In this section, we review some works that deal with query recommendation problems. These works are about two research communities. The first one concerns some works proposed in the BI community. The second community relates to works that address question recommendation problems in Web community Question Answering (CQA).

2.1 Recommendation in Business Intelligence

In recent decades, several recommendation approaches have been proposed in the BI community. The designed methods aim at recommending OLAP queries for DW's exploitation purposes. These methods can be classified into two categories: content based methods and collaborative filtering methods. The content based methods use the query log of an individual user, as in [14, 21]. The collaborative methods exploit the log file of multiple users as in[2, 15, 22, 43]. In addition, in [32], the authors propose a new concept named *"OLAP analysis context"* that targets reducing irrelevant recommended queries in order to improve OLAP recommendation systems. In [11], authors propose a collaborative recommender system based specifically on the user's interests. In this work, the user's requirements are expressed through a set of keywords which are discovered via the characterization of the interaction's intent with the BI system. The recommender system suggests a set of formal queries, provided on the basis of a model proposed to formalize the user's interest, clustering techniques, and Markov model which represents the probability for a user to switch from one interest to another.
Authors, in [12], propose an approach that aims to aims to hide the complexity of the structure of the Data mat to a decision-maker. To this end, the authors propose to generate a set of NL analytical queries for the semi-automatic derivation of the schema of a Data Mart. The generated analytical queries are built on the basis of a multidimensional pattern (MP). These queries are formed mainly with dimensions and their hierarchy levels Some of them are highly recommended than others due to the importance degree of the components (dimensions and hierarchies) provided with the MP. In this work, the authors focus more precisely on the generation of analytical queries rather than an automatic recommendation.

Most of the approaches presented above have emphasised on the recommendation of formal queries (SQL, MDX) that aim to query DWs from the formal ones as in [2, 15, 21, 22, 32, 43] and from a set of key words as in [11]. However, authors in [20], propose to integrate a feedback and recommendation mechanism (FRM) into BI tools (dashboards) in order to improve their ergonomics. This mechanism helps the user by generating textual and/or graphical visual cues, and thus leading the user to consider the use of certain data subsets and/or analysis forms [20].

2.2 Questions' recommendation in Web community Question Answering CQA

Web Community-based Question Answering such as (Yahoo! Answer, ask.com) web sites, online forums, and discussion boards [47], has become in the last decade a popular medium for online information seeking and knowledge sharing [39]. In a such community, a user posts a question and waits for answers from other users belonging to the same Q/A community or looks for questions that are similar to the prior asked question. However, with the exponential growth in data volume, it was becoming more and more time-consuming for users to find the questions that are of interest to them [39]. To cope with these challenging problems, several approaches and models have been proposed to perform automatic questions recommendation. Most of these works perform questions recommendation on the basis of the users' interest and with respect to questions that other users have answered or have asked.

Indeed, authors in [29] propose a recommendation approach based on a user-word model. To define this model, authors adopt the well known language model proposed in [37]. The user-word model aims to quantify the affinity between users and words in a questions' collection. This approach recommends questions on the basis of the evaluation of the question-user relationship in order to target eligible users.

In [17], the approach is based on a model dedicated for the user. This model captures the interest of a user and his authority in an area for Yahoo!Answer community. This model undergoes learning algorithms that investigate continually about the questions that have been previously answered by users in order to recommend the most similar ones.

Authors in [39] adopt a topic model in the recommendation approach as the probabilistic latent semantic analysis model (PLSA). This model aims to capture the most interesting topics for which a user cared about. The proposed approach analyses the characteristics of the user's question and exploits the questions historically asked in order to discover the topics to which a user may pay attention.

Authors propose in [49] an incremental algorithm that uses the PLSA model to perform automatic questions recommendation for the Wenda Chinese QA website. The authors define a set of criteria which the incremental algorithm operates: long and short terms of the interests of a user and the user's negative and positive feedback. The long terms are considered as all questions asked previously by a user, while short terms refer to the question asked newly.

In [1], the authors define a Fuzzy Relational Product Operation that measures the implication degree of a question between two questions. Authors combine this operation with the BM (Best Matching) similarity measure that calculates the similarity between the user's question and the sentences of answers.

In [19], authors propose a recommendation approach for the Oshiete goo Japanese QA community. This approach is based on the content based filtering and the collaborative filtering, applied on the history of both users' questions and answers. The authors define six features that support the recommendation system: (1) Probability to answer any questions in a category, (2) User-based collaborative filtering, (3) Item-based collaborative filtering, (4) Content-based filtering using answer histories, (5) Content-based filtering using question histories and (6) Probability of posting a question in a category.

In [28], authors propose to address recommendation problems through a method that measures similarity or diversity between questions by exploiting the notion of *"information needs"*. The authors adopt two topic models for predicting the information need as the translation model and the LDA (Latent Dirichlet Allocation) model.

In [51], authors propose a dual role model (DRM) that captures the different roles of a user (asker and answerer) in a community QA. This model is used to analyze the latent topic information with respect to the different roles by providing an accurate representation of the user. The DRM leads in recommending appropriate questions to the Top-and qualified users.

Authors in [50], propose to use the statistical language model in order to formalize the user's interest, according to his interest distribution over

the question's collection. Once the new question is asked in the community, a matching process is performed with the user's interests. This process is based on the query likelihood of the language model that calculates the degree of user interest in the new question.
In [13], authors propose a user intimacy model (UIM) and a novel topic model (*LDA-style*) that learn about intimacy between the users over topics through social interaction in CQA. These models allow to perform question recommendation through estimating the intimacy between a candidate user and an asker over a topic in a unified probabilistic framework.
Recently, the authors propose recommendation models [27, 44] that aim to deal with the problem of data heterogeneity and sparsity in CQA. Authors in [44] propose the JIE-NN model (Joint Implicit and Explicit Neural Network, JIE-NN) that combines explicit and implicit information based on multiple data sources. The authors consider heterogeneous explicit information sources to collaboratively learn user and item representations. In [27], authors propose *"AskMe"* as a system that merges two kinds of behavior levels in the CQA. Indeed, in this work, the authors propose to model the individual-level behavior interaction that captures the user's behaviors (e.g., answer, follow, vote) and the community-level behavior obtained according to the behavioral associations between similar users.

After studying all the works presented above, we summarize and compare them (see table 1) according to some criteria :

- *Input*: the user's query (the category of the query and the model formalizing the query) and the data/corpus needed by the recommendation approach;
- *what are the parameters on which the models adopted in the recommendation process are based:* the content (data/corpus) and the requirement (user's query and his profile);
- *Output:* the recommendation approach results
- *the objective:* the goal of the proposal.

By analysing the Table 1, we elucidate what follows:
(1) We can highlight that no work has specifically dealt with the recommendation of a decisional *Why-Question*;
(2) In the CQA community, the proposed approaches provides recommendations on the basis of models that consider the parameters: (a) the question inserted by the user (terms of interest); (b) the content (question's collection); and (c) the user's profile which is defined according to the user's center of interest. This latter is measured with respect to the questions asked and answered previously by the user. All these queries are gathered in a question's collection specific for the user;
(3) The questions recommendation approaches have adopted models as the language model and the topic models, that aim mainly at assessing similarities (syntactic, semantic, term's frequency) between the user's question and those located in the question's collection, in order to recommend the most suitable question. However, since these models focus only on the linguistic aspect, they unfortunately prove insufficient when it comes to deal with a decisional question in the BI context. Indeed, the most appropriate model to use in the *Why-Questions* recommendation process must take into consideration the multidimensional aspect of a DW that reveals the concepts of DW as well as the relations linking these concepts (fact table and its measures, measures and related dimensions, dimension and its hierarchy's levels and its attributes). For example, let suppose that a decision-maker asks a *Why-Question*, in which the focus of the question refers only to the DW's concept *"dimension"* as *"Why* ***customer*** *are more and more demanding in 2021"*, where the term "**customer**" references a dimention. While in our approach proposed in [16], the answering process needs a *Why-Question* that must contain the concept *"measure"* in order to be triggered. Thus, recommending a *Why-Question* as:*"Why has* ***internet order quantity*** *increased in 2021"* is necessary, where **internet order quantity** is a DW's measure related to the dimension **"customer"**.
(4) Consequently, we can't fully adopt the recommendation models adopted in the recommendation approaches proposed in the CQA community.
(5) In this context, we propose in this paper an approach for the recommendation of decisional NL *Why-Questions*, based on the parameters content (DW) and requirement (the *Why-Question* emitted by the decision maker). To perform the recommendations, we rely on a grammar that

Table 1 Related works

<table>
<tr><th colspan="4">Related works</th><th colspan="12">Web Question Answering
CQA</th><th colspan="2">BI</th><th rowspan="2">Our app</th></tr>
<tr><th colspan="4">Criteria</th><th>[49]</th><th>[17]</th><th>[39]</th><th>[19]</th><th>[1]</th><th>[28]</th><th>[51]</th><th>[29]</th><th>[50]</th><th>[44]</th><th>[13]</th><th>[27]</th><th>[12]</th><th>[11]</th></tr>
<tr><td>Input</td><td>NL user's query</td><td>Category</td><td>A set of key words</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td><td></td></tr>
<tr><td></td><td></td><td></td><td>Question: Decisional Why-Question</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td></tr>
<tr><td></td><td></td><td></td><td>Question: WH/Boolean Questions</td><td colspan="12">x</td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td>Model</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td><td>x</td></tr>
<tr><td></td><td>Data</td><td>Question's Collection</td><td></td><td colspan="12">x</td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td>Data Warehouse</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td><td>x</td></tr>
<tr><td></td><td></td><td>Multidimensional pattern</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td><td></td><td></td></tr>
<tr><td>Model based on</td><td>Requirement</td><td>User's query</td><td></td><td></td><td></td><td>x</td><td></td><td>x</td><td>x</td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td><td></td><td>x</td></tr>
<tr><td></td><td></td><td>User's profile</td><td></td><td></td><td>x</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>Content</td><td></td><td></td><td></td><td>x</td><td>x</td><td></td><td>x</td><td>x</td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td><td></td><td>x</td></tr>
<tr><td></td><td>Hybrid (requirements and content)</td><td></td><td></td><td>x</td><td></td><td></td><td>x</td><td></td><td></td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td><td></td><td>x</td><td></td></tr>
<tr><td>Output</td><td>Recommended queries</td><td>Existing NL queries</td><td></td><td colspan="12">x</td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td>Built Queries</td><td>Analytical query</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td></tr>
<tr><td></td><td></td><td></td><td>Decisional Why-Question</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td></tr>
<tr><td></td><td></td><td></td><td>Formal queries</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td><td></td></tr>
<tr><td>Objective</td><td>Performance</td><td></td><td></td><td>x</td><td></td><td></td><td></td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td><td>x</td><td></td></tr>
<tr><td></td><td>Relevance</td><td></td><td></td><td colspan="12">x</td><td></td><td>x</td><td>x</td></tr>
<tr><td></td><td>Perplexity</td><td></td><td></td><td>x</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>Cost</td><td></td><td></td><td></td><td>x</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>x</td><td></td><td></td></tr>
</table>

captures the DW's multidimensional aspect and formlises the *Why-Question* model proposed in [16]. This grammar is the core of our approach. Indeed, the proposed grammar is used first to perform the *Why-Question* analysis and therefore it guides the recommendation process. More details about our proposed grammar are presented in the following section

3 The Proposed Grammar for *Why-Question's* Analysis

In this section, we present our proposed grammar that aims at formalizing the content of a *Why-Question* [16] which principally refers to the DW's multidimensional concepts. To build this grammar, we adopt the linguistic patterns proposed by *"BARGUI and al"* in [4, 5]. More details regarding the proposed grammar are presented in the section 3.2 but we start first by reminding about the *Why-Question's* model proposed in [16] in the following section.

3.1 NL decisional *Why-Question* model

We consider a DW modelled in snowflake or in fact's constellation schema. It comports fact tables (F) composed of a set of measures (M) such as $M = \{m_1, ..m_i..m_n\}/i = 1..n$, a set of dimensions ($D$) such as $D = \{D_1, .D_j., Dt...D_m\}/$ $j = 1..m$ where Dt references a temporal dimension. Each D_j is described via a set of attributes (A) such as $A = \{a_1, ..a_k..a_p\}/k = 1..p$. A dimension D_j is provided or not with a level of hierarchy (L) such as $L = \{l_1, ..l_t..l_s\}/t = 1..s$, we note so a dimension as: $D_j[l_t^*[a_k]]$. To explain the model dedicated to a decisional *Why-Question* (Q), we have considered an actual DW *Microsoft Adventure Works-DW 2020* [1]. The Microsoft Adventure Works DW schema is illustrated in the figure 2. This schema concerns a DW designed and fuelled to cover sales, purchases, products, customers and some human resources. This DW includes several measures that can be analysed according several perspectives. The DW's measures relate to two main activities: *"Internet sales"* as well as *"Reseller sales"*. These measures are: *"Sales amount, Tax amount, Freight-transport, Order Quantity, Discount amount"*. A decision-maker can analyse the activity *"Internet sales"* according to the dimensions: *"customer, product, date, territory, currency, promotion"*. The *"Reseller*

[1] https://github.com/microsoft/powerbi-desktop-samples/blob/main/DAX/

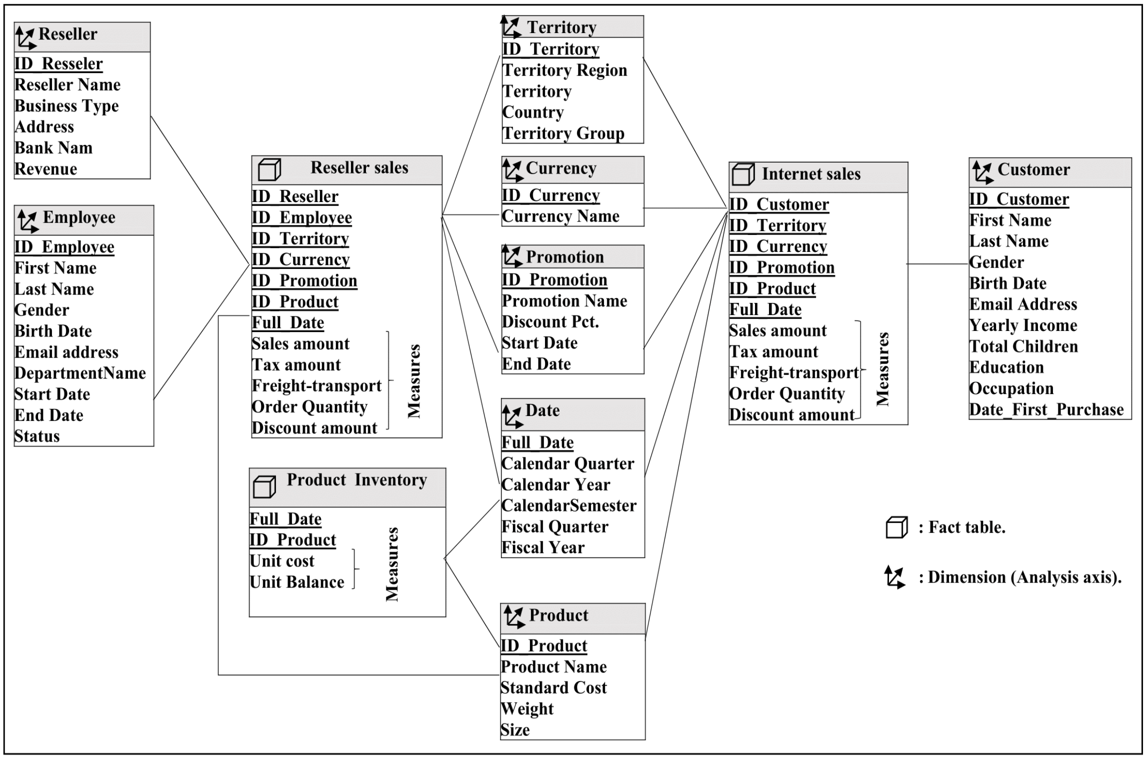

Fig. 2 Microsoft Adventure Works Data Warehouse-2020 schema.

sales" activity is concerned by the dimensions: *"employee, product, date, territory, currency, promotion, reseller"*. In addition, the decision-maker may be interested in the *"product inventory"*, for which the measures are *"unit cost* and *"unit balance"* and the dimensions are *"date, product"*.
We use the *"Microsoft Adventure Work DW 2020"* schema to unfold the proposed approach presented in the remainder sections.

After analysing the conceptual DW schema presented above, we have built a *Why-Question's* basis accessible at https://wq-bi.jimdo.com/. This questions' basis is produced from several combinations, made between the different components of the DW and according to questions those can be asked in company environment such as *"Why the company didn't evolve this year ?"*.

The *Why-Question* basis led us to model a decisional *Why-Question* according to its content. A decisional *Why-Question* is composed mainly of a set of DW's multidimensional elements (ME) (measures, dimensions, levels, members, etc.) that can be explicit or implicit. Therefore, we propose to classify a NL decisional *Why-Question* into two categories: explicit and implicit. In the first category, the measure M is explicit. In the second one, the measure M is implicit. Both of those categories are divided into two sub categories, where a dimension D_j is implicit or explicit. The corresponding examples are presented in table 2.

Based on the content of the *Why-Question's* basis and the *Why-question* classification presented above, we have modelled a decisional NL *Why-Question* (see the figure 3) as follows:

1. We model a *Why-Question* (Q) according to the multidimensional elements ME. Q must comport at least one *measure* M. The referenced *dimensions* are the *temporal dimension* Dt such as the *date* to specify the time

Table 2 Decisional *Why-Question* classification

Category	Sub-category		Examples
Explicit *Why-Question.*	Explicit measure	Implicit dimension	- Why has **internet sales amount** decreased? - Why have **internet sales and reseller's sales** decreased?
		Explicit dimension	- Why has **internet sales amount** decreased during the *years* comprised between 2018 and 2020? - Why has **internet sales amount** increased in *USA*?
Implicit *Why-Question.*	Implicit measure	Explicit dimension	- Why have *customers* become more and more demanding? - Why the *product p1* is sold more than the *product p2*? - Why do *employees* resign?
		Implicit dimension	- Why didn't the company evolve ?

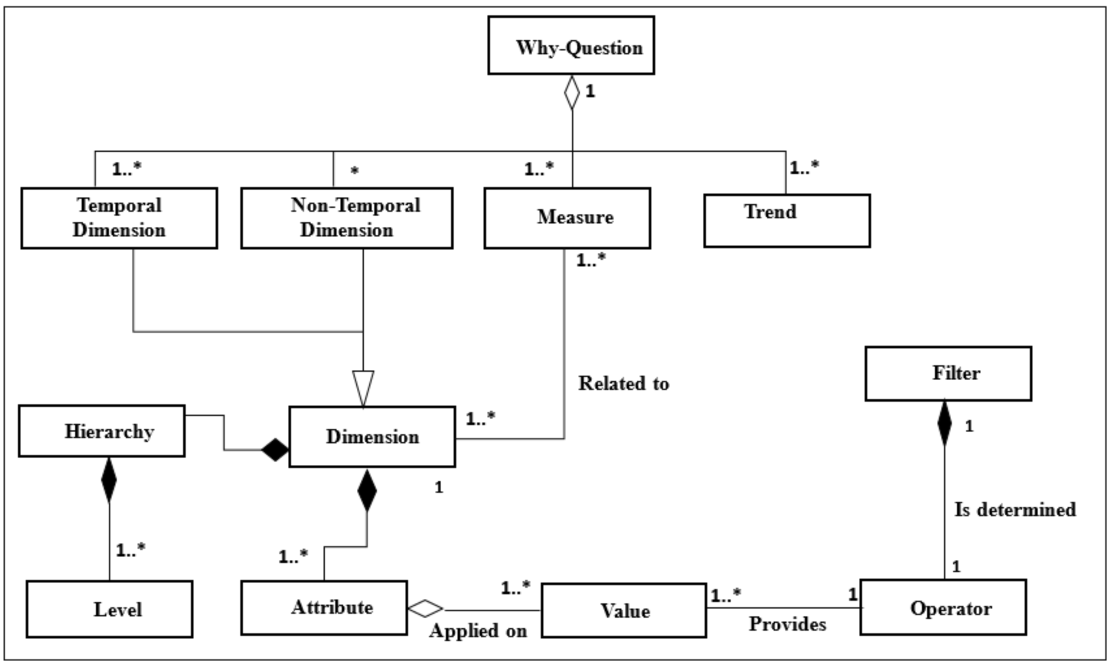

Fig. 3 Decisional NL *Why-Question* model.

and *non temporal dimensions* D_j such as *customer, product*. The specified dimension must be related to a measure in the analysis of a certain phenomena.

2. We always take into consideration the temporal dimension Dt in the *Why-Question* Q, whether or not is specified in this question. The temporal dimension is always present in DW. It is the most common and frequent analysis axis in a company.
3. In the analysis of the enterprise/organisation activity, the decision- maker is, in general, interested in a phenomena described through synthesized data that produce relevant observations and help in decision-making. These observations can be a set of *"trends"* derived from the DW's measures. Therefore, we include in the model the notion of *"trend"* (T). A *trend* is a changing observed on an activity during a given *period* such as: *decrease, increase, high, low, stagnation, change, stability*, etc. For example: *"Why has internet sales amount decreased" in 2020*?.
4. We consider that a *Why-Question* Q can comport filters (f). A *filter* f consists to apply a

restriction on the values (V) of the attributes of a dimension such as $V = \{v_1, ...v_e, ...v_r\}/e = 1..r$.

A filter f is defined according to a set of operators (OP) such as $OP \in \{$ *equals*, *between*, *less than*, *more than*, etc. $\}$. We note a filter $f : f[OP][D_j[l_t^*[[a_k[v_e]]]])$. For example *"Why has the internet sales amount decreased between 2015 and 2019"* where OP = *"between"* and *"2015, 2019"* is a filter to apply on an attribute of the dimension *"year"*.

3.2 Description of the Proposed Grammar

In this section, we describe our grammar proposed to overcome the difficulties related to the NL expression of a decisional *Why-Question*. This grammar contains a set of rules, governing the terminals and the non-terminals that refer to the components defined in the *Why-Question's* model (see section 3.1).

For the definition of our grammar, we have been inspired by the linguistic patterns proposed by *"BARGUI and al"* in [4, 6]. These patterns have been defined to handle the specifications of the dimensions expressed in a NL analytical query in order to generate semi-automatically the conceptual schema of a data mart in BI context. For example: *"Analyze the Turnover by shop's code, city and country"* where *"shop"*, *"city"* and *"country"* are dimensions.

In [4, 6], *BARGUI* shows that the linguistic patterns that specify *"dimensions"* are often expressed in a nominal form known as a nominal groups (NG), which can be defined as: (determinant + noun), (preposition + determinant+ noun), (preposition + determinant + noun + qualifying adjective), etc. such as: customer, product, country, postal code of a customer, etc. To define a generic form of these patterns, *BARGUI* propose a grammatical structure named **NG**, where:
;

NG:: = [determinant] NG1 [,[determinant] NG1,and [determinant] NG1] [determinant-preposition NG1] where **NG1** is the partial description of a dimension defined as: **NG1:: = Noun (Noun | Adjective| Past Participle| Preposition)***.

To define our grammar, we adopt the *BARGUI's* grammatical structure **NG**. However, **NG** concerns only the non temporal dimension's specifications. Hence, we extend **NG** in order to specify the multidimensional components *"measures"* and *"temporal dimension"* defined in the *Why-Question's* model presented in the section 3.1. In addition, we set in the proposed grammar, some rules that define the trends and the filters related to the *Why-Question*.

The figure 4 depicts the description of our proposed grammar. Square brackets indicate optional elements. The (*) indicates possible multiple occurrences of an element. GM is an optional string useful to complete the semantics of the question.

We describe the proposed grammar as follows:

1. A *Why-Question Q* refers to a set of non terminals that we set as follows:

   [Question-Pronoun](NG)[MG](trend's indicator)[MG](Filter)*

   . The non terminals *"NG"*, *"trend's indicator"* and *"Filter"* capture the important components of a *Why-Question* as: the measures, the temporal and non temporal dimensions and the trends. Indeed, with the non terminal **"NG"** placed after the Question pronoun *"Why"*, we can identify the *measures* expressed in the *Why-Question Q*. The non terminal *"Trend's indicator"* aims to locate the trends input in the *Why-Question Q*. Thanks to the non terminal *"Filter"*, we can target the expressed temporal and non temporal dimensions according to the grammatical structure *"NG"* or with respect to a set of rules that we detail in the rest of this section.
2. ***The measures*** are, in general, numerical attributes used in the calculation of the key performance indicators [4]. They are, in general, expressed in nominal forms with terms that indicate quantifications such as: quantity of milk, accident's number, internet sales amount, etc. Thus, we set in the grammar some lexicon called *"Measure's indicators"* that allow us to identify measures in the *Why-Question* such as: *"number, quantity, amount,*

Why-Question : : = [Question pronoun] (NG) [MG] (Trend's indicator) [MG] (Filter)*
Question pronoun :: =why
NG : : = [Determinant] NG1 [,[Determinant] NG1,… (Conj_Coordination) [Determinant] NG1] [Prepepsition Determinant NG1]
NG1 : : = Nominal_term (Nominal_term| Adjective| past participle| Preposition) *
Nominal_term:: = Noun | Measure's_indicator | Temporal_lexicon
Measure's_indicator : : = quantity| amount| total| number| volume| ratio| percentage | degree|…
Trend's indicator : : = decrease| increase| low| high| stagnation| stable| evolve| didn't evolve
Filter : : = Dimension_marker NG
| [Dimension_maker] Temporal_dimension
| Filter's_operator NG
| Filter's_operator Temporal_dimension
Dimension_marker : : = for| during | in| since| while| when| according to
Temporal _dimension : : = NG [Date] | Date
Temporal_lexicon ::= time| year| month| day| season| hour| minute| second…
Date : : = dd/MM/yyyy| MM/yyyy| dd| MM| yyyy| dd-MMM-yyyy| MMM-yyyy|MMM| MM/dd/yyyy | MMM dd, yyyy| MMM , yyyy
Filter's_operator : : = equal | more than| less than | with| this | between …and …
MG : : = string
Conj_coordination : : = and | or
Adjective : : = qualifying adjective
Preposition : : = of | at...
Determinant : : = a | of | of the | the...

Fig. 4 Our grammar proposed for the analysis of a NL *Why-Question*.

rate, total, percentage, etc.". To this end, we relied on a mathematical lexicon[2].

To reference a measure, we extend **NG1** into **NG1::= Nominal-term (Nominal-term | adjective| past participle | preposition)*** where **Nominal-term::= Noun | Measure's indicator**.

3. ***The trend*** is identified regarding a set of trend's indicators captured in a set of terminals as: *decrease, increase, high, low, stagnation, stable, evolve, didn't evolve, reduce, etc.*.
4. ***The filters*** are related to the temporal or to non temporal dimensions as described in the figure 4:

Filter::= Dimension-marker NG
|[Dimension maker] Temporal-dimension
| Filter's operator NG
| Filter's operator Temporal-dimension

The expressed filters can be identified with respect to:
(a) ***The non temporal dimensions*** that are detected using a set of dimension-markers that suits a decisional *Why-Question* such as:*"for, during, in, since, while, when, according to"*.
(b) ***The temporal Dimension*** that can be expressed in several ways:
- In a *"nominal form"* as: "the month of April, summer season,". Thus, we complete the rule **NG1** with the non terminal *"Temporal-lexicon"* where **Temporal-lexicon::= time|year |month|day|season|hour|minute| second**;
- With a temporal lexicon followed by a date such "the year 2018";
- *"Date format"* as "dd/MM/yyyy, dd-MMM-yyyy, MMM dd, yyyy, etc.".
(c) With respect to a set of operators expressed explicitly as:*"equal, more than, less than, with, this, between"*. These operators can be applied either on non temporal dimension or on temporal dimension
(d) The terms which are syntactically related to the prior identified dimension (NG) are considered as filters until another dimension marker is detected in the question. For example: "*in the city of Algiers*", where *"in"* is a dimension-marker, *"city"* and *"Algiers"* are related syntactically. Algiers is a value of the attribute of the dimension *"city"*.

4 Approach Description

In this section, we describe our proposed approach that recommends from a NL *Why-Question* asked by a decision-maker a set of NL ones. To this

[2] Alberta Education, Canada, 2015. Lexique de mathématiques - Mathematics Glossary

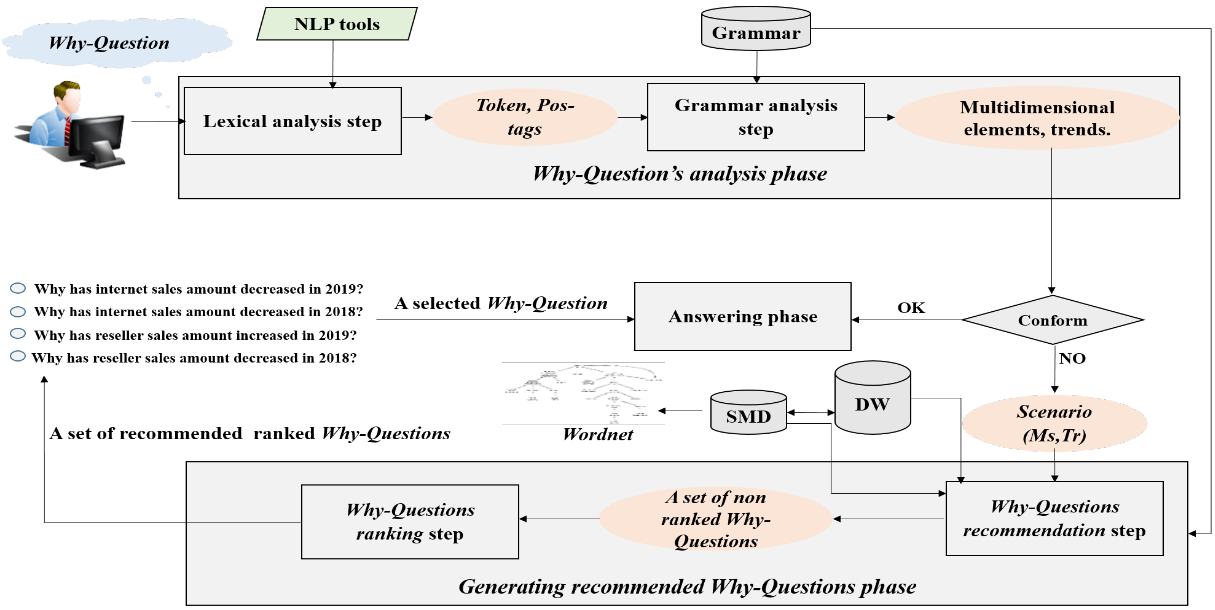

Fig. 5 Approach architecture.

end, a *Why-Question* analysis is required. This task is performed on the basis of the grammar presented in section 3.2. Our approach consists into two main phases: (1) *Why-Question* analysis and (2) Generating recommended *Why-Questions*. The details of each phase are presented in the rest of this section. The architecture of the approach is as illustrated in the Figure 5.

4.1 *Why-Question* Analysis Phase

The objectives of this phase is to obtain a set of relevant terms or phrases that characterize the *Why-Question* Q. It includes two steps: (1) the lexical analysis step and (2) the grammar analysis.

4.1.1 Lexical Analysis Step

This step aims to identify from the NL text: the tokens of the question and their morpho-syntactic labels *"POS (Part Of Speech) tags"*. This can be performed by using existent POS Taggers like the *StandFord Pos Tagger*, due to its high accuracy which is 97 % [30]. A label is then attached for each token of the question. This label refers to a POS tags such as: (Det) for Determinant, (NN) for Noun, (Adj) for Adjective, (Prep) for Preposition and (PP) for Past Participle Verb, etc.
Example:
Let suppose the *Why-Question* (Q_1): *"Why has internet sales amount decreased in 2019?"*. The lexical analysis of this question produces what is described in the table 3. Thus, the lexical analysis

Table 3 Lexical analysis outputs

Question's term	Pos-Tag	Signification
Why	WP	WH interrogative pronoun
has	VBZ	Verb conjugated in the present tense with the 3rd singular person
internet	NN	Singular noun
sales	NNS	Plural noun
amount	NN	Singular noun
decreased	VBN	Verb, past participle
in	IN	Preposition or subordinating conjunction
2019	CD	Cardinal number
?	/.	Question end mark

step takes as input a the *Why-Question* expressed in NL and returns as output a tagged question as: Q'_1: *" Why/WRB has/VBZ internet/NN sales/NNS amount/NN decreased/VBN in/IN 2019/CD?/. "*
These labels will be used at the grammatical analysis step. More details are presented in the following section.

4.1.2 Grammar Analysis Step

The syntax analysis and the use of a set of indicative keywords improve the *Why-Question* answering [46]. Hence, we use the grammar presented in section 3.2 in order to identify the most important text's fragments on which we must focus to provide the *Why-Question's* answers. These text's fragments must refer to the multi-dimensional elements ME (measure, dimensions, temporal dimension and filters) as well as trends as defined in the *Why-Question* model. To capture the details of the grammar analysis step, we propose the Algorithm 1 as presented below:

- We emphasize on the spotting out the nominal groups NG expressed in the Why-Question Q.
- A nominal group NG can refer either a dimension (temporal D_t or non temporal D) and a measure M.
- When a NG comports a measure's indicators as defined in our grammar (quantity, total, number, etc) then this NG refers to a measure (lines 2 and 3).
- We identify dimensions (line 4 in the algorithm 1) thanks to a set of dimensions markers (per, since, according to, etc). These dimensions can be either temporal or non temporal and they refer to filters expressed in the *Why-Question* as explained in the section 3.2. Thus, if after a dimension maker, a date or temporal lexicon are expressed, then this *Why-Question's* Q fragment refers to a temporal dimension D_t (lines 6 and 8). When no temporal lexicon is expressed after a dimension maker then a non temporal dimension D is identified (line 12).
- When it remains in the *Why-Question* Q non identified texts with respect to the conditions presented above, two functions are invoked: *Filters identifying* (line 13) and *Trend's identifying* (line 14), as presented in the Algorithms 2 et 3 respectively.

Algorithm 1: Grammar analysis

Input: Q: NL decisional Why-Question;
Output: M: measures, D: non temporal dimensions, Dt: temporal dimensions.
Intermediate variables: i: integer; NG: set of nominal group, initially empty;
Begin
1. **While** (it is not the end of Q)
    Begin
2. **If** Q contains Measures indicator **then**
3. $M \leftarrow M \cup NG_i$; // NG_i contains a measure's indicator. It refers to a measure.
4. **If** Q contains dimension marker **then**
5. **If** after dimension marker Q contains Date **then**
6. $Dt \leftarrow Dt \cup date$;
// date refers to a temporal dimension D_t.
7. **Else**
8. **If** after dimension marker Q contains temporal lexicon **then**
9. $Dt \leftarrow Dt \cup NG_i$; // This NG_i refers to a temporal dimension D_t.
10. **Else**
11. **If** after dimension marker Q contains NG_i **then**
12. $D \leftarrow D \cup NG_i$; // This NG_i refers to a non temporal dimension D.
13. Filter's identifying (Q);
14. Trend's identifying (Q);
    End
End

The Algorithm 2 comports the following steps:

- Identifying the filter's operators ({ equal, more than, less than, with, }) with respect to the corresponding rule defined in the grammar presented in section 3.2 (line 2).
- Testing then if after the identified operator of filter, it exists a date or a nominal group NG that corresponds respectively to a temporal dimension D_t (line 4) or a non temporal dimension D (line 7).

Algorithm 2: Filters identifying

Input: Q: The NL decisional Why-Question:
Output: Dt: temporal dimensions; D: dimensions;
Intermediate variables: i: integer;
Begin
1. **While** (is not the end of Q)
    Begin
2. Identifying filter operator; ; // filter's operator ={ equal, more than, less than, with, }
3. **If** after filter operator it exists Date **then**
4. $Dt \leftarrow Dt \cup Date$; // date refers to a temporal dimension D_t.
5. **Else**
6. **If** after a filter operators it exists nominal group NG_i **then**

7. $D \leftarrow D \cup NG_i$; // This NGi refers to a non temporal dimension D.
End
End

Once the filter's identifying Algorithm is performed, the Algorithm 3 will be triggerd. It takes as input the terms remained in the *Why-Question* Q in order to identify the expressed trends in Q. This algorithm performs then a syntactic comparison between these terms and the trend's indicators defined in the grammar, using the *Levenshtein* similarity measure [10, 41] (line 2).

Algorithm 3: Trend's identifying
Input: Q: NL decisional Why-Question;
Output: T: sets of trends, initially empty;
Intermediate variables: i: integer;
Begin
1. **While** (is not the end of Q)
Begin
2. **If** a $term_i$ is similar to a trend's indicator **then**
3. $T \leftarrow T \cup term_i$ // This term refers to a trend.
End
End

Applying the algorithms 1, 2 and 3 with respect to the *Why-Question* $Q_1^{'}$: *" Why/WRB has/VBZ internet/NN sales/NNS amount/NN decreased/VBN in/IN 2019/CD?/. "* produces a syntactic tree as illustrated in the figure 6. Thus, the multidimensional elements ME are: D_t =< 2019>, M =< internet sales amount>, and the trend is T =< decreased >.
Let's suppose another example of a *Why-Question* as (Q_2): *"Why has order quantity of reseller sales decreased in 2020 in the city of Algiers?"*, produces the information: D =< the city of Algiers >, D_t =< 2020>, M =< order quantity of reseller sales> and T =< decreased >.
The *Why-Questions* Q_1 and Q_2 comport all the essential elements either the multidimensional elements ME (measure, temporal dimension and non-temporal dimension) and trend T. Hence, these *Why-Questions* are able to trigger the answering process. However, a contrary scenario is quite sure since the decision-maker is generally not always aware of the DW's lexicon. Thus, the decision-maker can ask the *Why-Question* (Q_3): *"Why didn't the company evolve?"*. By applying the algorithms 1, 2 and 3 on this question, we obtain: $D =< \emptyset >$, $D_t =< \emptyset >$, $M =< \emptyset >$ and T =< didn't evolve >. In this case, the grammar analysis indicates us that Q_3 doesn't conform to the *Why-Question's* model and consequently it will be not possible to trigger the answering process. To remedy this issue, we lean towards a *Why-Questions'* recommendation phase, which is based on both the decision maker requirement (his question) and the DW's content, guided by the results obtained after performing the grammar analysis step. More details regarding this phase are presented in the remaining section.

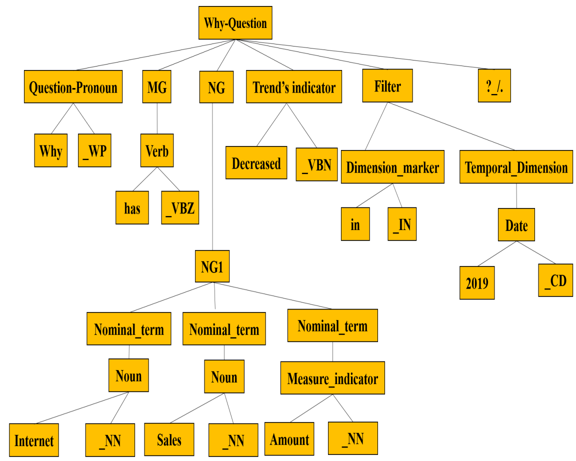

Fig. 6 Syntactic tree generated using our proposed grammar.

4.2 Generating Recommended *Why-Questions* Phase

This phase aims to recommend from the question input by the decision-maker and the grammar analysis results, one or multiple *Why-Questions*. This phase consists into two steps: (1) the *Why-Questions* recommendation step and (2) *Why-Questions* ranking.

4.2.1 *Why-Questions* Recommendation Step

Once the *Why-Question* analysis is performed, two cases are possible: (1) the question is conform to the *Why-Question's* model. In this case, the answering process is triggered (our approach proposed in [16]);

(2) the *Why-Question* doesn't conform to its model (a *Why-Question* without measure, trend or temporal dimension);
To cope with the second case, we propose to recommend to the decision-maker a set of *Why-Questions*. We formalize the recommendation process as a function $Recommend(Q;\ S;\ DW - content) \rightarrow Q_R$ where:

- Q: is the decision-maker's NL *Why-Question* and Q_R: is a set of recommended *Why-Questions.*
- S: is a scenario materialised as $S =< M_s, T_r >$ where:
  - M_s are messages indicating the shortcomings identified in the *Why-Question* which are produced from the grammar analysis step such as: *"there is no measure, no temporal dimension or no trend".*
  - T_r is formalised as:
  $$T_r = \begin{cases} \emptyset \; when\ no\ important\ terms\ remain \\ in\ Q \\ Set\ of\ important\ terms\ extracted \\ from\ Q \end{cases}$$
  An important term ($t \in T_r$) is mainly a *nominal group NG* that remains non identified after the *Why-Question* analysis phase. With the assumption that a measure M is the key element of a *Why-Question*, thus, a term t is considered as a candidate measure (M_c).
- *DW-content*: to capture the DW lexicon, we propose a Structure of multidimensional data called (*SMD*). The *SMD* is loaded automatically from the OLAP schema of the DW. It comports *labels* that specify each information loaded in the *SMD* such as *fact, measure, dimension, dimension's attributes, level.* To represent the links existing between the multidimensional elements ME existing in the DW, we use a binary code as follows:
  $$\begin{cases} \mathbf{1}\ when\ it\ exists\ a\ link\ between\ two\ ME \\ (\ measure\ and\ dimension\ ,\ two\ levels\ , \\ \ measures\ and\ fact) \\ \mathbf{0}\ otherwise \end{cases}$$
  The decision-maker formulates his *Why-Question* through a set of terms expressed in NL. These latter may not exist in the *SMD*, but correspond to other terms that are semantically close. To remedy this problem, we propose to use an external resource as the *Wordnet* ontology. To this end, we define a function that retrieves the terms that are semantically similar for each term loaded in the structure *SMD*. This semantic similarity is established, in this paper, only on the basis of the synonymy relation (the synonym set *"Synsets"*) of the *Wordnet* ontology.
  To recognize the values of the non temporal dimensions i.e attributes values (Named Entity Recognition) that remain non identified in the *Why-Question Q*, we access the DW via a set *SQL* queries. By the means of these queries, we perform the adequate research operations through the indexes of the corresponding non temporal dimensions.

On the basis of the function "*Recommend*" presented above, given a *Why-Question Q* and a scenario $S(M_s, T_r)$, we recommend a set of *Why-Questions* Q_R. The recommendation process is performed with respect to the following variants:

- ***Variant 1:*** When M_s is a *"temporal dimension's gap"* then the initial *Why-Question* is completed with a temporal reference. This reference concern the (n) last years.
  Example: Let consider the question (Q_4): *"Why has amount of reseller sales decreased?".* The *Why-Question* analysis phase returns what follows: measure M= { *amount of reseller sales"*}, T= {*"decreed"*}, M_s= { *"Temporal dimension gap"*}. Consequently, the recommended *Why-Questions* are going to be: *"Why has amount of reseller sales decreased in 2019?", "Why has amount of reseller sales decreased in 2020?".*
- ***Variant 2:*** When M_s is a *"trend's gap"* then we recommend a set of *Why-Questions* attached with the adequate trend's indicators. The most appropriate trend's indicator is determined with respect to a mathematical model named *trend' function* that we have proposed in [16]. This model aims to generate the most interesting overall trends such as an increase, a decrease or stagnation. These trends provide a qualitative perception on the multiple variations of the measure's values ($M[V]$) observed according to the interval specified by the temporal dimension *Dt*. The measure's values ($M[V]$) are retrieved thank to an SQL query executed on the DW.
  The model *"trend' function"* describes mathematically the data (Xi, Yi), where X is the

time interval defined according to the dimension Dt and Y represent $M[V]$. The *"trend' function"* is based on the principle of non-linear regression, for which the curve does not necessarily go through all the coordinates (xi, yi) but approaches them as much as possible. It allows to perform a good descriptive approach and to obtain the desired precision without being hindered by the multiple local oscillations of Yi.
To build the *trend' function* defined as: $f(Xi) = Yi$, we have to look for the value of the relative error R, described as:

$$R = \sqrt{\frac{\sum_{i=0}^{k}(Y_i - f(Xi))^2}{k}} \tag{1}$$

Where k is the number of the coordinates (Xi, Yi) .
Let the polynomial form as :
$f(x) = P^n(x) = \sum_{j=0}^{n} a_j x^j$.

The ideal function $f(x)$ is obtained, when R reaches its minimum value. This is performed, when the partial derivatives of R vanish simultaneously:

$$\left[\frac{\partial R}{\partial a_0} = 0, ..., \frac{\partial R}{\partial a_j} = 0, ..., \frac{\partial R}{\partial a_n} = 0\right] \tag{2}$$

This equation's system leads us to fix the parameters $\{a_j\}$.
Once the trend function is determined, it becomes possible to perform a standard function's study that highlights the different aspects such as: high peak, low peak, decrease and increase with their respective intervals and the amplitude of the variations ΔY. **Example:** Let suppose the *Why-Question* (Q_5):*"Why did not we achieve an important amount of internet sales in 2019?"*. The *Why-Question* analysis phase supplies what follows: measure M= { *amount of internet sales"*}, M_s= { *"Trend's gap"*}. By applying the trend's function on the measure "amount of internet sales", we have found two trends: *"decrease"* and *"increase"* as illustrated in the figure 7. These observations are then recommended to the decision-maker in the form of a set of *Why-Questions*.

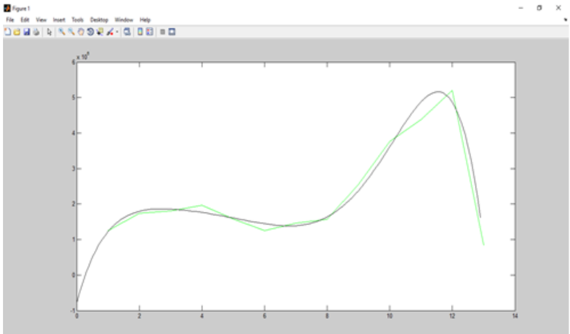

Fig. 7 The trends observed for the measure "internet sales amount" during 2019.

- ***Variant 3:*** When M_s is *"measures' gap"*, each term $t \in Tr$ considered as a candidate measures M_c is parsed regarding all the measures collected in the structure *SMD*. This is performed in order to look for similar instances. A string matching is then accomplished using a measure's similarity. We consider in this paper the Levenshtein distance (several NL approaches opted for this measure as in [10, 41]). When no measure is founded, the same process is performed first with *dimensions* and then with the levels of the dimension's hierarchy .
When the string matching process fails, a semantic mapping is triggered to look for terms semantically similar in the *"Wordnet"* ontology. This variant engenders two cases as follows:
  - ***Case 1:*** Once a similar instance to the term t is detected as a multidimensional ME (dimension or level) then all the measures M related to this ME are extracted to carry out the recommendation.
    Example: (Q_5): *"Why clients are more and more demanding?"*. In this question, the recognised terms are *"client"*. This term refers semantically to the dimension *"Customer"*. Consequently, the recommended *Why-Questions* are generated according to the related measures to *"Customer"* such as: *"Why has order quantity of internet sales increased in 2020?"*, *"Why has internet sales amount increased in 2020?"*.
  - ***Case 2:*** When the term t doesn't correspond to any multidimensional elements ME, we recommend a set of

Why-Questions resulting from a combination between all the DW's measures with the adequate trends indicators attached with a temporal reference. This may generate an important number of questions. Therefore, we propose to return a set of generic questions. These questions are built on the basis of the *"fact names"*. The decision-maker selects the most closet question to his need. We recommend then the corresponding *Why-Questions* attached with the measures related to the chosen activity (fact).

Example: let suppose the *Why-Question* (Q_6): *"Why didn't the company evolve?"*. The question's analysis phase produces the results: Trend's indicator $T=$ "didn't evolve", $M_s=$ { *"measures gap, temporal dimension gap"*}, T_r={"company"}. Applying the recommendation approach, we have found that the term *"company"* doesn't correspond to any multidimensional element ME. Here some generic questions: *"Do you want analysing internet sales?","Do you want analysing reseller sales?"*. If the decision-maker selects the question: *"Do you want analysing internet sales?"*, then one of the recommended *Why-Questions* is: *"Why has internet sales amount decreased in 2020?"* where *"internet sales amount* is a measure and *"2020"* is the temporal reference.

4.2.2 *Why-Questions* Ranking

The recommendation step returns a set of *Why-Questions* without order. We propose so to rank the recommended *Why-Questions* on the basis of a scenario $S(M_s, T_r)$ as follows:

- When M_s=*"temporal dimension gap"* then the *Why-Questions* are ranked with respect to a descending order of the temporal reference.
- When M_s=*"trends gap"*, we sort the questions in an increasing order of the trends.
- When M_s=*"measure gap"*, tow cases are possible:
  - The ranking is performed according to a descending order of the similarity rate between t and the identified measures. However, when t references a measure M and a non temporal dimension D_j, the priority is given first to the measures and then to the non temporal dimensions because in our approach we focus mainly on the concept *"measure"* as proposed in the *Why-Question's* model. For example, let suppose that t="production" which is similar to the dimension *"Product"* and the fact table *"Product Inventory"*. In this case, we recommend first a set of *Why-Questions* attached with the measures of the fact table *"Product Inventory"* and then the measures related to the dimension *"Product"* (internet sales amount, reseller sales amount, etc).
  - When t doesn't correspond to any multidimensional element ME, we return a set of *Why-Questions* attached with the measures of the fact table chosen by the decision-maker. These questions are ranked with respect to the measures as they are loaded in the structure *SMD* i.e as they are defined in the OLAP schema of the DW.
- When M_s include several indications, we combine all the instructions presented above to rank the recommended *Why-Questions*. The priority is given first to the identified measure M. Then, we associate for this measure M the adequate trend T provided with the appropriate temporal reference.

Once the recommended *Why-Questions* are ranked, they are returned to the decision-maker. Thereafter, this latter will choose the closest question to his need in order to trigger the *Why-Quesion's* answering process.

5 Experimental Study

In order to test our approach, we have realised a tool called *"WQ-Recommender"* by using the languages *JAVA* and *Matlab* in the *NetBeans IDE 8.0.2* environment. In order to implement the proposed grammar, we have used the *ANTLR* framework [3] (ANother Tool for Language Recognition). As a data set, we have exploited the *"Microsoft AdventureWorks-DW*

[3] https://www.antlr.org/

2020"[4] through the *Microsoft SQL Server*. The *"WQ-Recommender"* tool allows the decision-maker via its graphical interface to express his Business need in the form of a NL *Why-Question*. This tool returns to the decision-maker a set of recommended *Why-Questions* right after the analysis of the input question. A screen shot of the *"WQ-Recommender"* tool is as shown in figure 8.

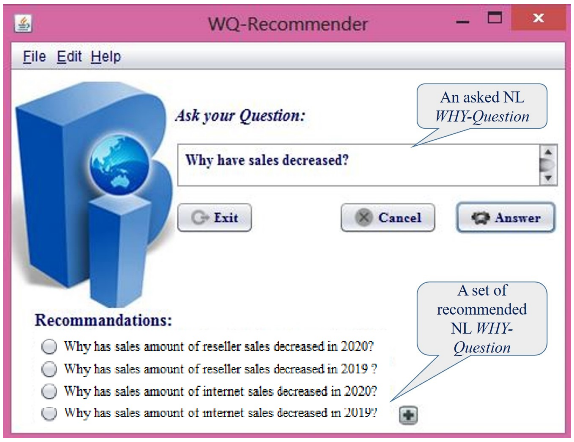

Fig. 8 *WQ-Recommender* Tool screen shot.

For evaluation purposes, we have asked for a set of users of our dataset (members of our laboratory) to formulate a basis of NL *Why-Questions*. The *Why-Questions'* basis is accessible at https://wq-bi.jimdo.com/. It comports 30 *Why-Questions* Q. On the basis of the *Why-Question* model, we propose to classify the *Why-Questions* basis into 6 categories as follows:

- **Category 1** (CT_1): this category refers to *Why-Questions* Q that comport measure M but without trend's indicator T ($Q =< M, Dt, T^- >$) like *"Why did not reseller achieve an important amount of sales in 2020? "*.
- **Category 2** (CT_2): in this category, the terms of the *Why-Question* Q reference a measure M and a trend's indicator T but no temporal dimension Dt is mentioned ($Q =< M, Dt^-, T >$) such as *"Why has internet sales amount decreased?"*.
- **Category 3** (CT_3): the *Why-Questions* Q of this category don't contain a measure ($Q =< M^-, Dt, T >$). For example: *"Why has sales decreased in 2019?"*.
- **Category 4** (CT_4): the *Why-Questions* gathered in this category don't have measure and trend's indicator T ($Q =< M^-, Dt, T^- >$) such as *"Why the promotions that we made this year did not bring us much?"*.
- **Category 5** (CT_5): the *Why-Questions* do not have measure, temporal dimension and trend's indicator ($Q =< M^-, Dt^-, T^- >$) as *"Why are customers more and more demanding?"*.
- **Category 6** (CT_6): the *Why-Questions* don't include measure and temporal dimension ($Q =< M^-, Dt^-, T >$). For instance: *"Why didn't the company evolve?"*.

On the basis of the *Why-Question's* categories presented above, we evaluate the *relevance* of the proposed approach as well as the *ranking* method of our proposal.

5.1 Relevance Evaluation

In order to assess the quality of the recommendations, we have involved the same users who have defined the *Why-Question's* basis, in judging the relevance of our approach. For this end, we have asked these users to select from a set of recommended *Why-Questions* with respect to a *Why-Question* that belongs to the question's basis, the questions that are closest to their needs. A *Why-Question* is judged relevant if it is selected (chosen) by a user. This means that this question is close to the decision-maker's need. A *Why-Question* is considered more relevant than another if and only if it is selected by several users.
To this end, we consider the metrics: recall (R) and precision (P). We propose to interpret R and P as follows:

- The metric *"Recall"* R allows to answer the question: "How many relevant *Why-Questions* Q are selected by users (U)?" formula (3).

$$R = \frac{NumberOf\ Same_Q\ Selected\ by\ All_U}{NumberOf\ Selected_Q\ by\ All_U} \tag{3}$$

In order to calculate the recall R, we must investigate with respect to a *Why-Question*, about the recommended *Why-questions* that have been selected by all users. Then, according to these choices, we must look for about the

[4]https://github.com/microsoft/powerbi-desktop-samples/blob/main/DAX

same questions selected by all users. In this case, the relevance is expressed by the proportion of the users' same choices among all their selected *Why-Questions*.

- The metric *"Precision"* P enables to answer the question: "How many selected *Why-Questions* Q are relevant?" formula (4).

$$P = \frac{NumberOf\ Same_Q\ Selected\ by\ All_U}{NumberOf\ Q_R} \quad (4)$$

We remind that Q_R is the set of *Why-Questions* recommended by our approach.
To calculate the precision P, we have to search about the same recommended *Why-Questions* that have been chosen by the all the user among all the *Why-Questions* recommended by our approach.

Table 4 captures the average values of the recall R and the precision P with respect to the six *Why-Question's* categories presented above.

Table 4 Recall and Precision result's evaluation

	CT_1	CT_2	CT_3	CT_4	CT_5	CT_6
R	1	0,5	0,5	0,52	0,5	0,33
P	0,33	0,4	0,25	0,26	0,24	0,21

This experimental study shows that our approach provides, on the one side, with respect to the recall R, the following results:

- A good recall R, since its average value i "1" for the category 1. This is because this category of questions include all the decisional indicators except the trend indicator. This means that there is same consensus between all users.
- Moderate results are recorded for the categories 2,3,4,5. These values that $\in [0.5, 0.52]$ are justified by lack of one or more decisional indicators.
- A value of 0.33 concerns the category 6. This low result is explained by the absence of all the decisional indicators. In this case, our approach returns multiple questions related to the fact table chosen by the decision-maker. These questions reflect, thus, scattered needs. Therefore, the users will not have the same choices (same requirements) and the criterion of relevance is called into question.

On the other side, with respect to the metric precision P, we notice what follows:

- The average value of the precision P varies from 0,21 to 0,4. These results mean that more the decision-maker question is vague (categories 3,4,5 and 6) more it proves difficult to meet the decision-maker's needs. Indeed, if for example, the content of the decision-maker question references only dimensions like *"Why customers are more and more demanding ?"* while our approach recommends questions that focus only on "measures", the selection of a recommended *Why-Question* becomes subjective.
- Sometimes the decision-maker wonders about phenomena whose explanation is not necessarily found in the DW such as: *"Why has the demand of the after-sales service increased"*. In this case, our approach provides results that seem divergent to the decision-maker. Otherwise, our system can help the decision-makers to point out some design insufficiencies of the DW to the *IT-Designer* for future exploitations.

5.2 Comparison with a Recommendation Approach based on NL modelling

In order to support the results of relevance presented above, we compare our proposal with a model adopted in the recommendation approches proposed in the Web Question Answering community CQA. Two main models have been adopted in CQA approaches: the language model (LM) adopted in [29] and [50] and the topic models as: the probabilistic latent semantic analysis model (PLSA) [39, 49] and the Latent Dirichlet Allocation (LDA)) [28]. In our context, the model that we can adopt is the language model LM proposed in [37]. By employing this model in our context, we want to show up until what limits this model can satisfy a decisional need when we consider only the linguistic aspect of the question.

The language model LM has been proposed by [37] for Information Retrieval. It has been widely applied in many applications. This model aims to rank a relevant document d by the probability of generating the query terms in their language models [9]. This model calculates $P(q|M_d)$ which evaluates the probability of a query (q) given the language modelling LM of document (d). This

LM is used to assign a likelihood to a user's query $q = (q_1, q_2, ...q_m)$ where $(q_1, q_2, ...q_m)$ is a sub query equivalent to set of terms $(t_1, t_2, ..., t_m)$. The probability of a term t given a document d is related to the frequency of t in the document d. The probability of a query $q = (q_1, q_2, ...q_m)$ is the product of the individual terms probabilities $P(q|d) = \prod_i P(q_i|d)$ [8] which is equivalent to $P(q|d) = \prod_{(t\in q)} P(t_i|d)$. The relevance of a document d to a query q is presumed to be monotonically related to $P(q|d)$ [8].

The probability $P(q|M_d)$ has been defined as follows:
$P(q|M_d) = \prod_{(t\in q)} P(t|M_d) * \prod_{(t\notin q)} 1 - P(t|M_d)$, where:
We have first to estimate the maximum likelihood (P_{ml}) defined as the probability of term t under the term distribution for document d.
$P_{ml}(t|M_d)$ has been described as follows:
$P_{ml}(t|M_d) = tf_{(t,d)}/dl_d$, where:
$tf(t, d)$ is the raw term frequency of a term t in a document d; dl_d is the total number of tokens in a document d.

In our work, we adopt the language model LM presented above as follows:
- We replace the query q by a *Why-Question* Q and the document d by a question $(Q^{'})$ that belongs to a collection of *Why-Questions* (C). This collection C is a basis built from the *Why-Questions* that have already been answered by our approach proposed in [16]. This basis is accessible at https://wq-bi.jimdo.com/.
- We employ thus the language model LM as follows:
$P(Q|M_{(Q^{'}\in C)}) = \prod_{(t\in Q)} p(t|M_{(Q^{'}\in C)}) * \prod_{(t\notin Q)} 1 - p(t|M_{(Q^{'}\in C)})$.
- By analogy to the CQA recommendation approach, we set a similar scenario i.e. we recommend on the basis of the adopted language model LM a set of NL *Why-Questions* $Q^{'}$, from the *Why-Question* Q and the collection of *Why-Questions* C.

For example, let us suppose that we have a *Why-Question's* collection C composed of four questions:

- $Q^{'}_1$: Why has internet sales amount decreased in 2019?1
- $Q^{'}_2$: Why has reseller sales amount increased in 2019?
- $Q^{'}_3$: Why reseller tax amount increase this year?
- $Q^{'}_4$: Why has reseller sales amount decreased?

With respect to the collection C, we apply the language model LM on the *Why-Questions* (Q_7): *"Why sales decreased ?"* and (Q_8): *"Why are customers more and more demanding?"*. In order to recommend the most relevant question $Q^{'}$, we have to calculate $P(Q|M_{(Q^{'}\in C)})$. The obtained results are captured in the table 5.

Table 5 Adopting the language model LM in our context.

$P(Q\|M_{(Q^{'}\in C)})$	$Q^{'}_1$	$Q^{'}_2$	$Q^{'}_3$	$Q^{'}_4$
Q_7	0.66	0	0	0.5
	Recommended questions: $Q^{'}_1$, $Q^{'}_4$			
Q_8	0	0	0	0
	No question is recommended			

We notice that the language model LM does not recommend any question for Q_8 while it is possible to recommend the question $Q^{'}_1$ with our approach. Indeed, the term $t=$ "customer" refers to the multidimensional element dimension D for which we can recommend questions attached with the related measures as the "internet sales amount" (see figure 2). Thus, these results show that the language model LM can not be always sufficient to recommend decisional questions because it is mandatory to consider the multidimensional aspect of the DW.

To compare our proposal and the approach based on the language model LM presented above, we calculate the recall R and the precision P as proposed in section 5 (see table 6).

Table 6 Precision and Recall of both approaches.

		CT_1	CT_2	CT_3	CT_4	CT_5	CT_6
Our app	P	0,33	0,4	0,25	0,26	0,24	0,21
	R	1	0,5	0,5	0,52	0,5	0,33
LM	P	0,2	0,07	0,11	0,045	0,12	0,011
	R	0,5	0,2	0,2	0,18	0,16	0,15

After comparing the results of the recall R and the precision P produced by our approach and that based on the language model LM, we notice that our approach provided better results in terms of relevance.

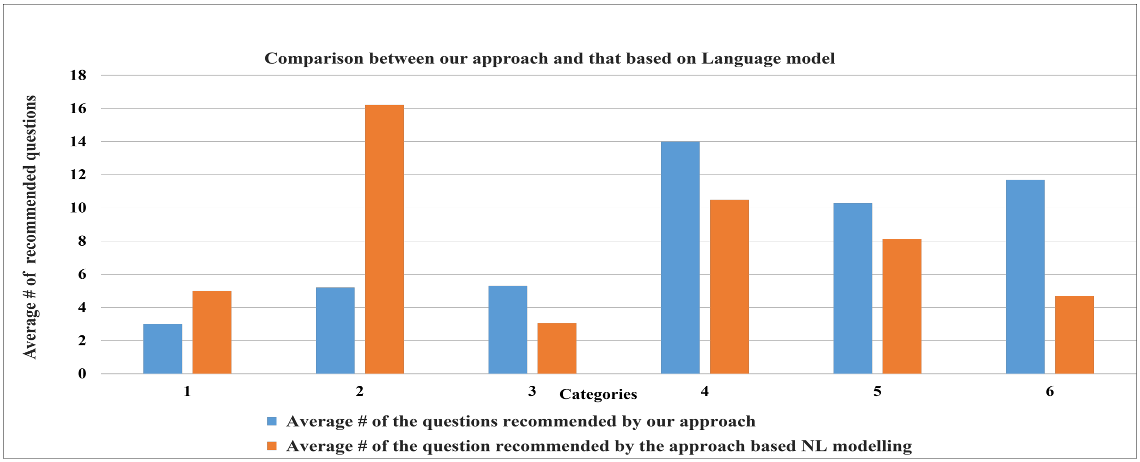

Fig. 9 Comparison between our approach and that based on the language model LM

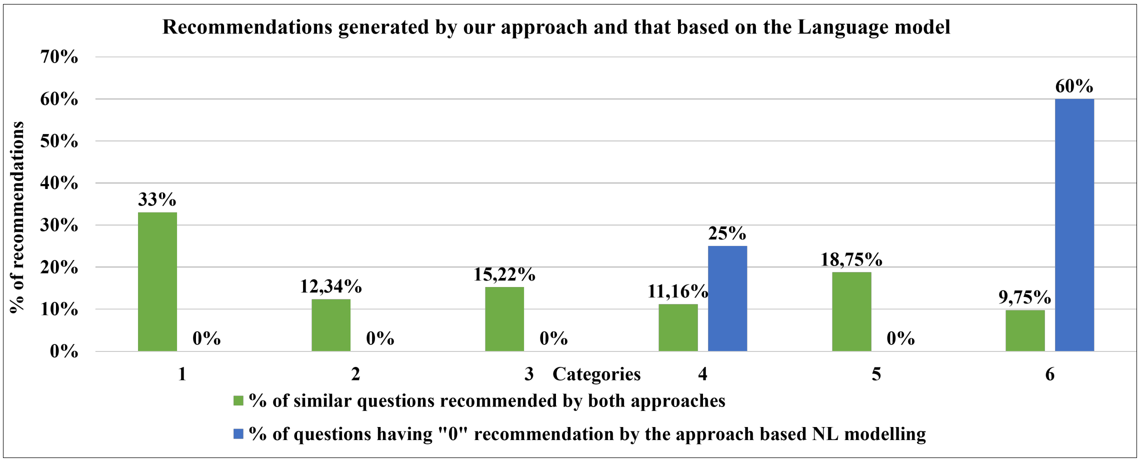

Fig. 10 Recommendations generated by our approach and that based on the language model LM

In addition to the assessment of the relevance presented above, we performed an experiment that compares our approach and that based on the language model LM with respect to:

- The average number of the recommended questions as captured in figure 9.
- The percentage of similar questions recommended by the two approaches as well as the percentage of questions for which no question is recommended (see figure 10).
- We consider that two *Why-Questions* are similar if and only if they include at least the same measure M and the same trend indicator T.

According to the results illustrated in the figures 9 and 10, we elucidate what follows:

- On one hand, the figure 9 shows that when the need of the decision-maker is precise as the *Why-Questions* that belong to the categories 1 and 2, our approach is more efficient than the one based on the language model LM. Indeed, we have found that the language model LM encumbers the decision-maker with questions that are not necessarily satisfactory. This is explained by the fact that the approach based on theLM, recommends questions Q' according to the frequency of a term $t \in Q$ in a question Q'.
  The similarity rate of the questions recommended by the two approaches, amounts to a percentage that varies between 12% and 33% (see figure 10).

- On the other hand, when the need of the decision-maker is not precise like the *Why-Questions* of the categories 3,4,5 and 6, our approach recommends more questions than the second (see figure 9). This is explained by the fact that, in the recommendation process, we insist on the DW's multidimensional aspect (relation between a dimension and measures, between a measure and a fact table, etc.). While the second recommendation approach emphasizes only on the linguistic similarities between the decision-maker's need and the collection of questions C.
  In this case, the figure 10 shows that the similarity rate of the questions recommended by the two approaches is between 9.75% and 18.75%. However, we notice that 23.33% of the questions remain without any recommendations with respect to the approach based on the language model LM.

5.3 Ranking Evaluation

To evaluate the ranking method, we have solicited the same users involved in the relevance evaluation. We have asked these users to set their ranking only for their selected (chosen) *Why-Questions*. We have then compared their ranking with that of our approach by performing a set of tests. These tests consist in investigating about each *Why-Question* selected and ranked by the user if it is well positioned or not with respect to the others *Why-Questions* ranked by our approach. To this end, we propose the following formula:

$$Tst{-}ranking = \frac{number\ of\ correct\ orders}{Total\ of\ performed\ tests} \quad (5)$$

To explain the formula 5, we describe the set of tests in the Algorithm 4 as follows:

Algorithm 4: Ranking test

Input: Q_S: a set of recommended *Why-Questions*; Q_U: a set of selected and ranked *Why-Questions* by a user;
Output: Test-ranking: float;
Intermediate variables: s, u, n, number of correct ranking, Total of performed tests, Total of correct ranking: integer;
Begin

1. number of correct ranking=0;
2. Total of performed test= 0;
3. Total of correct ranking=0;
4. **For** (u =2 to n)
   Begin
4. **For** (s= 1 to (u-1))
   Begin
5. If Position of (Q_U) > Position of (Q_S) **then** // Q_U is well ranked with respect to Q_S
   Begin
6. number of correct ranking ++;
   End
7. Total of performed tests++;
8. Total of correct ranking=Total of correct ranking+ number of correct ranking;
   End;
   End;
9. Test-ranking= Total of correct ranking/Total of performed tests;
End

For example, let suppose that our system recommends 5 *Why-Questions*: Q_1, Q_2, Q_3, Q_4 and Q_5. These questions are ranked by the user as follows: Q_2, Q_1 , Q_4 , Q_3 and finally Q_5. We notice for example that Q_2 is ranked by the user before Q_1, but it is well placed regarding Q_3, Q_4 and Q_5. Thus, the number of correct ranking for Q_2 is 3. We perform then same process for each question to obtain Test-ranking= 8/10.

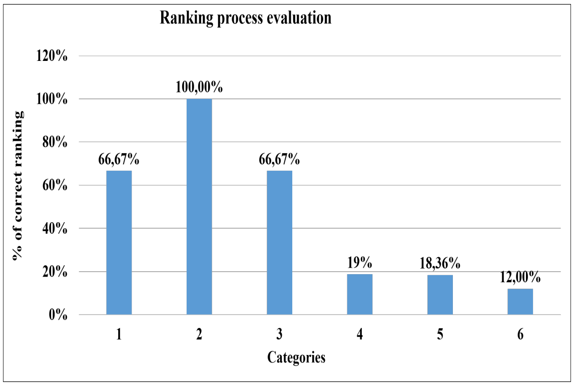

Fig. 11 Ranking process evaluation

The figure 11 shows the percentage of well ranking regarding the six categories of the *Why-Question's* basis used in the relevance evaluation. We notice that the more the decision-maker's

Why-Question is precise (more decisional indicators), the more the ranking approach is effective. Indeed, for example, with respect to the sixth *Why-Question's* category where the questions are vague, i.e questions without decisional indicators, the percentage of well ranking is 12 %. This is due to the fact that the selection of the suggested *Why-Questions* is subjective. Consequently, the user's ranking regarding the chosen *Why-Questions* becomes subjective too.

6 Conclusion and Future Works

Business Intelligence is the key technology that ensures effective decision-making. In this context, we have proposed a recommendation approach that supports the NL querying process of a DW. Our approach deals with the recommendation problem of decisional *Why-Questions* expressed in natural language. We propose to see this problem as the call to a function *"Recommend"* which considers the two parameters *"the decision-maker's requirement (Why-Question)"* and *"the DW's content"*. The function *"Recommend"* computes a set of *Why-Questions* ranked according to their relevance. To recommend the most appropriate NL *Why-Questions*, we rely on a grammar that suits the *Why-Question's* model proposed in [16].

To validate our proposal, we have developed the *"WQ-Recommender"* tool. Our tool allows the decision-maker to formulate his *Why-Question* in NL and provides him with a set of recommended NL *Why-Questions*.

In order to assess the quality of the provided recommendations, we have evaluated the relevance of our approach by involving decision-makers. To support the obtained results, we have compared our approach with a recommendation approach based on the language model adopted in the Web Question Answering community CQA. The obtained results show that if the multidimensional aspect of the DW is not considered, the recommendation process fails. In addition, we have proposed an evaluation metric for the ranking process.

Currently, we are working on the integration of an *"Ontology"* component in our approach in order to improve the recommendation process in terms of performance and relevance. This *"Ontology"* component is built automatically. Its concepts are the DW's multidimensional elements (fact, measure, dimension, level) and its individuals are the instances of these concepts. The relations between the concepts of this ontology are determined with respect to the DW's structure (the measures and the fact table they belong to, the measures and the related dimensions, the dimension and its levels). In addition, we enrich this ontology with other concepts according to the semantic relations: *"Synonym of, Meronym of, Hyperonym of, Antonym of, Is-a"*. We aim to use this ontology as follows:
First, to validate the identified multidimensional elements by our grammar. This will be performed through querying the ontology with *SPARQL* instead of iterating several data structures. For example, when a term is identified as a *"measure"*, we query the ontology to confirm if this term is an instance or not of the concept *"measure"*.
Secondly, when a term doesn't correspond to any multidimensional element, we compare it with the rest of the ontology's concepts through the semantic relations. For example: since the decision-maker can express his need with terms that are too vague such as *"Why are persons more and more demanding?"*, where the term *"person"* can reference the dimensions *"customer"*, *"employee"* or *"reseller"* with respect to the semantic relation *"Is-a"*. In this case, our approach will recommend a set of *Why-Questions* attached with the measures related to one of the chosen dimension instead of generating question regrading to the fact tables. Hence, the recommendation approach will be able to provide questions that will be closer to the need of the decision-maker.

As future work, we plan to integrate the *"user's profile"* in the recommendation process. The user profile enables to prune some non-relevant *Why-Questions* (do not suit the profile). Actually, we intend to consider in the user profile two parameters: (1) measures of interest and (2) decision's type;

1. Since we focus on the concept *"measure"* in the recommendation process, we will thus handle the history of the measures with which the decision-maker has previously interacted through his asked *Why-Questions*.
2. We consider the type of decisions that the decision-maker can make with respect to his

role in a company (strategic, tactic and operational). The decision's type can lead to recommending the most suitable *Why-Question* according to the appropriate "hierarchy level" with respect to the requested *"dimension"*.

Declarations

- **Funding:**
  The authors did not receive support from any organization for the submitted work.
- **Conflict of interest/Competing interests:**
  The authors have no relevant financial or non-financial interests to disclose.
  The authors have no competing interests to declare that are relevant to the content of this article.
- **Ethics approval:**
  'Not applicable'
- **Consent to participate:**
  'Not applicable'
- **Consent for publication:**
  'Not applicable'
- **Availability of data materials:**
  Authors declare that all data and materials are available.
- **Code availability:**
  Authors declare that the software application is available and it supports their published claims and complies with field standards.
- **Authors' contributions**
  All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by *Guessoum Meriem Amel, Djiroun Rahma* and *Kamel Boukhalfa*. The first draft of the manuscript was written by *Guessoum Meriem Amel* and *Djiroun Rahma* and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

References

[1] Ahn CM, Lee JH, Choi B, et al (2010) Question answering system with recommendation using fuzzy relational product operator. In: Proceedings of the 12th International Conference on Information Integration and Web-based Applications & Services, ACM, pp 855–858

[2] Aligon J, Gallinucci E, Golfarelli M, et al (2015) A collaborative filtering approach for recommending olap sessions. Decision Support Systems 69:20–30

[3] Baral C, Ha Vo N, Liang S (2012) Answering why and how questions with respect to a frame-based knowledge base: a preliminary report. In: LIPIcs-Leibniz International Proceedings in Informatics, Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik

[4] Bargui F, Feki J, Ben-Abdallah H (2008) A natural language approach for data mart schema design. In: Proc. of 9th Int. Arabic Conference on Information Technology (ACIT), Hammamet-Tunisia

[5] Bargui F, Ben-Abdallah H, Feki J (2016) A natural language-based approach for a semi-automatic data mart design and etl generation. Journal of Decision systems 25(4):309–344

[6] Bargui F, Ben-Abdallah H, Feki J (2016) A natural language-based approach for a semi-automatic data mart design and etl generation. Journal of Decision systems 25(4):309–344

[7] Barzdins J, Grasmanis M, Rencis E, et al (2016) Self-service ad-hoc querying using controlled natural language. In: International Baltic Conference on Databases and Information Systems, Springer, pp 18–34

[8] Berger A, Lafferty J (2017) Information retrieval as statistical translation. In: ACM SIGIR Forum, ACM, pp 219–226

[9] Chou TC, Chen MC (2008) Using incremental plsi for threshold-resilient online event analysis. IEEE transactions on Knowledge and Data Engineering 20(3):289–299

[10] Djiroun R, Bimonte S, Boukhalfa K (2015) A first framework for top-k cubes queries. In: International Conference on Conceptual Modeling, Springer, pp 187–197

[11] Drushku K, Aligon J, Labroche N, et al (2019) Interest-based recommendations for

business intelligence users. Information Systems 86:79–93

[12] Feki J, Ben-Messaoud I (2009) Nl-pi: A natural language tool for the reuse of multidimensional patterns. In: The International Conference on Information Technologie

[13] Fu C (2020) User intimacy model for question recommendation in community question answering. Knowledge-Based Systems 188:104,844

[14] Giacometti A, Marcel P, Negre E, et al (2011) Query recommendations for OLAP discovery-driven analysis. IJDWM 7(2):1–25. https://doi.org/10.4018/jdwm.2011040101, URL https://doi.org/10.4018/jdwm.2011040101

[15] Golfarelli M, Rizzi S, Biondi P (2011) myolap: An approach to express and evaluate olap preferences. IEEE Transactions on Knowledge and Data Engineering 23(7):1050–1064

[16] Guessoum MA, Djiroun R, Boukhalfa K (2017) Dealing with decisional natural language why-question in business intelligence. In: 8th International Conference on Information and Communication Systems (ICICS), IEEE, pp 52–57

[17] Hu D, Gu S, Wang S, et al (2008) Question recommendation for user-interactive question answering systems. In: Proceedings of the 2nd international conference on Ubiquitous information management and communication, ACM, pp 39–44

[18] Imhoff C, White C (2011) Self-service business intelligence. Empowering Users to Generate Insights, TDWI Best practices report, TWDI, Renton, WA

[19] Kabutoya Y, Iwata T, Shiohara H, et al (2010) Effective question recommendation based on multiple features for question answering communities. In: ICWSM

[20] Kaur B, Singh V (2020) Increasing bi capabilities with frm based recommendations. Solid State Technology 63(6):18,353–18,367

[21] Khemiri R, Bentayeb F (2013) Fimioqr: Frequent itemsets mining for interactive olap query recommendation. In: The Fifth International Conference on Advances in Databases, Knowledge, and Data Applications (DBKDA), Citeseer, pp 9–14

[22] Kozmina N (2013) Adding recommendations to olap reporting tool. In: ICEIS (1), pp 169–176

[23] Kuchmann-Beauger N (2013) Question answering system in a business intelligence context. PhD thesis, Ecole Centrale Paris

[24] Kuchmann-Beauger N, Aufaure MA (2011) A natural language interface for data warehouse question answering. In: Natural Language Processing and Information Systems. Springer, p 201–208

[25] Kuchmann-Beauger N, Aufaure MA (2011) Structured data-based q&a system using surface patterns. In: International Conference on Flexible Query Answering Systems, Springer, pp 37–48

[26] Lawton G (2006) Making business intelligence more useful. Computer 39(9):14–16

[27] Li N, Guo B, Liu Y, et al (2021) Askme: joint individual-level and community-level behavior interaction for question recommendation. World Wide Web pp 1–24

[28] Li S, Manandhar S (2011) Improving question recommendation by exploiting information need. In: Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, Association for Computational Linguistics, pp 1425–1434

[29] Liu G, Hao T (2012) User-based question recommendation for question answering system. International Journal of Information and Education Technology 2(3):243

[30] Manning CD (2011) Part-of-speech tagging from 97% to 100%: is it time for some linguistics? In: Computational Linguistics and

Intelligent Text Processing. Springer, p 171–189

[31] Naeem MA, Ullah S, Bajwa IS (2012) Interacting with data warehouse by using a natural language interface. In: Natural Language Processing and Information Systems. Springer, p 372–377

[32] Negre E, Ravat F, Teste O (2018) Olap queries context-aware recommender system. In: International Conference on Database and Expert Systems Applications, Springer, pp 127–137

[33] Oh JH, Torisawa K, Hashimoto C, et al (2012) Why question answering using sentiment analysis and word classes. In: Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, Association for Computational Linguistics, pp 368–378

[34] Oh JH, Torisawa K, Hashimoto C, et al (2013) Why-question answering using intra- and inter-sentential causal relations. In: ACL (1), pp 1733–1743

[35] Oh JH, Torisawa K, Kruengkrai C, et al (2017) Multi-column convolutional neural networks with causality-attention for why-question answering. In: Proceedings of the Tenth ACM International Conference on Web Search and Data Mining, ACM, pp 415–424

[36] Pechsiri C (2016) Explanation based why question answering system. In: Proceedings of the International MultiConference of Engineers and Computer Scientists

[37] Ponte JM, Croft WB (1998) A language modeling approach to information retrieval. In: Proceedings of the 21st annual international ACM SIGIR conference on Research and development in information retrieval, ACM, pp 275–281

[38] Popowich F, Mosny M, Lindberg D (2012) Interactive natural language query construction for report generation. In: Proceedings of the Seventh International Natural Language Generation Conference, Association for Computational Linguistics, pp 115–119

[39] Qu M, Qiu G, He X, et al (2009) Probabilistic question recommendation for question answering communities. In: Proceedings of the 18th international conference on World wide web, ACM, pp 1229–1230

[40] Rajesh J, Babu PC (2021) Significance of natural language processing in data analysis using business intelligence. In: Deep Natural Language Processing and AI Applications for Industry 5.0. IGI Global, p 169–188

[41] Saias J, Quaresma P, Salgueiro P, et al (2012) Binli: An ontology-based natural language interface for multidimensional data analysis. Intelligent Information Management 4(5)

[42] Sangroya A, Saini P, Rawat M, et al (2019) Natural language business intelligence question answering through seqtoseq transfer learning. In: Pacific-Asia Conference on Knowledge Discovery and Data Mining, Springer, pp 286–297

[43] Singh A, Parimala N (2014) Recommending next query in an olap session. In: Computational and Business Intelligence (ISCBI), 2014 2nd International Symposium on, IEEE, pp 73–80

[44] Tu H, Wen J, Sun A, et al (2018) Joint implicit and explicit neural networks for question recommendation in cqa services. IEEE Access 6:73,081–73,092

[45] Vashisht V, Dharia P (2020) Integrating chatbot application with qlik sense business intelligence (bi) tool using natural language processing (nlp). In: Micro-Electronics and Telecommunication Engineering. Springer, Singapore, p 683–692

[46] Verberne S, Boves L, Oostdijk N, et al (2008) Using syntactic information for improving why-question answering. In: Proceedings of the 22nd International Conference on Computational Linguistics-Volume 1, Association for Computational Linguistics, pp 953–960

[47] Wang X, Huang C, Yao L, et al (2018) A survey on expert recommendation in community question answering. Journal of Computer Science and Technology 33(4):625–653

[48] Watson HJ, Wixom BH (2007) The current state of business intelligence. Computer 40(9):96–99

[49] Wu H, Wang Y, Cheng X (2008) Incremental probabilistic latent semantic analysis for automatic question recommendation. In: Proceedings of the 2008 ACM conference on Recommender systems, ACM, pp 99–106

[50] Xianfeng Y, Pengfei L (2016) Question recommendation and answer extraction in question answering community. International Journal of Database Theory and Application 9(1):35–44

[51] Xu F, Ji Z, Wang B (2012) Dual role model for question recommendation in community question answering. In: Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval, ACM, pp 771–780

Meriem Amel Guessoum is a Ph.D. Student at the University of Science and Technology Houari Boumediene (USTHB), Algiers, Algeria. She is a member of the ISI research team at the LSI laboratory. She received the Master Degree in Computer Science from the USTHB in 2011 and the Bachelor Degree in Computer Science from the same university in 2009. She is currently teaching Computer Science as temporary teacher at USTHB and others establishments. Her current research interests include Data Warehouse, Business Intelligence, Natural language, Information Retrieval, Recommendation Systems and Causality.

Rahma Djiroun is currently a Lecturer and Researcher in Computer Science at the University of Sciences and Technology Houari Boumediene (USTHB), Algiers, Algeria. She is a member of the ISI research team at the LSI laboratory. She received the Ph.D diploma from the USTHB in 2019. She received her Engineer and Magister Degree in Computer Science from the USTHB in 2002 and 2005, respectively. In 2005, she joined the Faculty of Electronics and Computing, USTHB University, as an Assistant Teacher. Her current research interests include Data Warehouse, OLAP, Business Intelligence, Natural language, Information Retrieval, Cloud Computing and Recommendation Systems.

Kamel Boukhalfa is currently a Full Professor and researcher at University of Sciences and Technology Houari Boumediene, Algiers (USTHB). He is a member of the ISI research team at LSI laboratory. He received the engineer diploma in Computer Science from USTHB in 1997, the master degree in Computer Science from the same university February 2002. He joined, in 2002, the Advanced Technology Development Research Center for the development of Tele-health projects. He received the Ph.D diploma from Poitiers (France) and USTHB (Algeria) Universities in 2009. He received the accreditation to supervise research (HDR) from USTHB February 2011. His main research interests are Big Data, data bases, data warehousing, Cloud Computing, data mining and optimization.

Elhadj Benkhelifa is Full Professor of Computer Science at Staffordshire University and its Head of Professoriate. He is the Founding Director of the Smart Systems, AI and Cyber security Research Centre and the Cloud Computing and Applications Research Lab. He has published 150+ research outputs in journals, conference and as book chapter and has co-edited 20+ Conferences proceedings and special issues or reputable journals. He is an international speaker and a co-founder of a number of pioneering IEEE indexed international conferences. He is Senior Member of IEEE, Member of ACM and member of the Advisory board for the West Midlands Cyber Resilience Centre.