# Increasing the Effectivity of Business Intelligence Tools via Amplified Data Knowledge

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**Abstract:** Decisions based on data are crucial for the successful operation of modern companies. The fundamental part of decision making and knowledge creation is the business intelligence process. The effectivity of business intelligence tools depends on many factors. One factor of major importance is data quality. From the perspective of business intelligence data quality is related to multiple dimensions including those connected to the understanding of data. The aim of this paper is to improve the data understanding process in the existing typical business intelligence architecture by adding specific knowledge layers. An explicit data knowledge layer should be connected to the existing metadata layer. Data governance principles suggest setting up an ownership structure in data processes which also allows access to tacit knowledge. The practical value of the inclusion of the suggested knowledge layers in the existing business intelligence architecture is confirmed via a real business case study from the banking sector. The selected case study reflects the manner in which the current metamodel contributes to the big data phenomenon by improving its value element within the context of collaborative decision making in big organizations by using quality data that stems from tacit knowledge, and via a synergetic functionality of business intelligence and knowledge management.

**Keywords:** Business intelligence, Data knowledge, Data quality, Tacit knowledge, Explicit knowledge, Metamodel.

## 1. Introduction

Data and information are a crucial part of the everyday routines of most companies. Better data usage is considered one of the sources of economic growth (Henderson et al., 2017). There are more reasons for the importance of data. What connects these reasons is knowledge – knowledge of the company, its clients, and their competitors' behaviour. If a company wants to be successful, it needs two essential things: high-quality data and previous knowledge (Liu et al., 2018). Data governance and data quality management have become an integral part of companies' strategy (Lepri et al., 2017).

The return to the importance of data quality management came after the retreat to quantity preference in big data concepts. However, some works show that companies cannot abandon quality if they are dealing with various data sources (Ardagna et al., 2018) or for big data specific processes (Merino et al., 2016). Generation of metadata can improve contextual data quality (Zuiderwijk et al., 2016). In addition to preserving the meaning of data, metadata answers questions related to other dimensions of data quality: where the data comes from, how old it is, who created it, or who modified it (Lawrenz et al., 2019). Automatic metadata generation is crucial for rapid and effective decision making (Sundarraj & Natrajan, 2019).

Modern organisations rely heavily on systems and platforms that facilitate extraction, processing, transformation, hosting, and analysing significant data volumes generated at high speed. The goal of these systems, known as business intelligence (BI), is to create new values (Atanasijevic & Milosevic, 2020) and support decision making (Zaraté, 2008). BI solutions also include metadata repositories which provide information about the sources, time and format of the generated data (Aljumaili et al., 2016). However, individual BI layers for hosting explicit knowledge related to the processes supported by BI solutions are missing. Explicit knowledge that stems from BI experts and process owners' tacit knowledge can significantly ameliorate metadata quality and boost the performance of a BI solution.

### Goal and Structure

This paper aims to create an improved BI metamodel. An explicit knowledge layer will be included in it based on the description and the analysis of data and knowledge factors necessary for the proper functioning of the business intelligence process and for creating new knowledge. The proposed metamodel attempts to enrich the standard BI architecture and ameliorate the synergetic functionality of BI and KM concepts. Such a synergy improves the "value" element of the big data phenomenon in the context of effective organizational collaborative decision making (Filip et al., 2017). The usefulness of the metamodel is tested by applying it in real business situations. In order to achieve the aforementioned goal, the following structure has been determined.

https://doi.org/10.24846/v30i2y202106 

In Section 2 of this paper, the basics of data quality are summarised along with its linkage to knowledge. The data quality potential to include the storage (and sharing) of knowledge about the data itself is also explained.

Section 3 focuses on the description of the business intelligence (BI) process. Several factors are determining the effectiveness of BI solutions. Data quality is one of these factors and determines the BI system's success (Yeoh et al., 2008). Also, the theoretical background of interconnections between knowledge management (KM) and BI solutions is described.

In Section 4 the incorporated tools and methods are delineated. In Section 5 the research results are thoroughly explained. The classical BI concept is enriched by knowledge layers. Moreover, the new metamodel's usefulness is verified in the authors' survey of the real business situation. The results from the responses indicate the importance of BI enrichment. The metamodel enrichment is employed for adding new flows in the conceptual BI process model. Section 6 sets forth the summarised conclusions regarding the usefulness of this research.

## 2. Interconnections Between Data Quality and Knowledge

The concept of "data" itself has undergone a historical semantic change. The primary (statistical) definitions of the term data explain it as a coded representation of facts about the surrounding world (Henderson et al., 2017). Another definition of data quality could be related to the data statistical processing and to its added informative value.

Theories of knowledge provide another view of data, where data is the basis of knowledge creation. In these theories, data is considered an external object's property (Baskarada & Koronios, 2013). More important than data itself is information quality. The level of performance of the data-information-knowledge-wisdom chain measures information quality.

Any digitised information or knowledge is considered "data" in computer science. Data quality takes on a technological dimension. It has been linked to the development of databases since the 1980s. Data (and knowledge) storage has since been associated with problems such as record referencing, deduplication and record pairing (Madnick et al., 2009).

Data in companies is of all the above types. A separate field of study was created, which examines data quality in relation to several dimensions. The motivation was the economic impact of low data quality, which reaches tens of percent of the company's total costs (Orr, 1998).

The interest in data quality in business practice is associated with the growing importance of systems and databases, as data quality was not ideal in them (Klein et al., 1996). This situation has led to the building of centralised enterprise solutions. Also, centralisation made it possible to detect low data quality that was neither detectable nor measurable in local data repositories (Xu et al., 2013). The second source of interest in data quality management was expanding the Internet and unifying the quality of data disseminated by this network (Naumann, 1998).

For both reasons above, complex data quality concepts are emerging. The first and most frequently cited is the Strong-Wang framework which is based not only on the technical side of data quality but on a broader concept of data use (Strong et al., 1997). It contains the basic idea of defining multiple dimensions of data quality and dividing them into groups or categories. A key term that appears here and is agreed upon by other authors is the level of data quality, which can be measured as "fitness-for-use" (in the nomenclature of some authors "fitness-for-purpose", e.g. Henderson et al., 2017). This principle is rather general, and it has been applied to data quality (Best & Neuhauser, 2006).

The principle of "fitness for use" emphasises the subjective side of data quality (Scannapieco & Catarci, 2002) and states that data quality depends on its usage. A possible reason for this opinion is that data cannot capture reality in an absolute manner because reality is continuously changing, and data becomes obsolete from the moment of reality capture. This concept introduces knowledge in two ways - evaluating the possibility of acquiring knowledge from data and the need-to-know data for its usage. This idea is represented in the Strong-Wang concept of data quality (Figure 1) as Values-added and Ease of understanding.

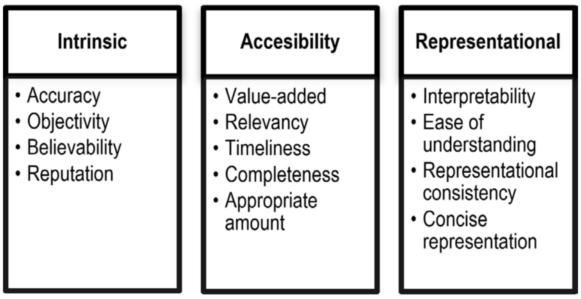


**Figure 1.** Data quality categories and dimensions. Based on Strong et al. (1997)

Other data quality frameworks also refer to data understanding. The review of twelve frameworks for measuring data quality from 1996 to 2000 found "data understanding" in seven of them (Spruit & Linden, 2019. The "understandability" dimension of data quality proved itself to be an essential one. However, as it is a subjective dimension, it is not easy to define what one could imagine under this data requirement.

Another theoretical area within data-knowledge is metadata (generally defined as data about data). This is a means of increasing contextual data quality. Metadata is transformed into an efficient decision-making process that in turn results in high performance outcomes (Shankaranarayanan et al., 2006). Industry 4.0 leads to digitisation and drives a broader spectrum of processes creating metadata (Trașcă et al., 2019). Metadata can store information related to data quality, such as expected values in a field, expected format, checksums, or rules, which allows for advanced automatic checks (Visengeriyeva & Abedjan, 2018). Automatic metadata generation speeds up computing performance and simplifies data users' work (Sundarraj & Natrajan, 2019).

## 3. Knowledge and BI Solution Interlink

### BI and KM Concepts

In the classical approach, BI solutions are perceived as sources of knowledge creation using data in companies (Moscoso-Zea et al., 2016). Some frameworks link knowledge management (KM) and BI solutions. This link is mostly "sequential" (e.g. Moscoso-Zea et al., 2016). The link goes through BI results – knowledge. This knowledge is then shared using KM tools. At the same time, implicit knowledge is the basis for querying BI solutions thereby closing the circle. However, there is little interaction between the BI process itself and previously-stored knowledge (or tacit knowledge). This paper aims to change this situation by creating a framework describing a much deeper connection between KM and BI.

The idea that BI-type processes (like data mining, knowledge discovery from databases) cannot be performed without prior knowledge is not new. Frameworks describing the acquisition of knowledge from data tend to be iterative and cyclical, which presupposes a certain degree of self-learning and storage of information and knowledge about the process itself.

One example is the Cross-Industry Standard Process for Data Mining (CRISP-DM). This process is initialised by understanding the business situation and the data (Wirth & Hipp, 2000). Following steps include data processing and modelling. Then the cycle returns to its beginning and provides a better understanding of the business situation. The understanding of the whole business situation is closely connected with the understanding of data. There is also a transfer of knowledge regarding data as such, albeit indirectly.

By extending the Knowledge Discovery from Database (KDD) process with data quality and prior knowledge, the DQPK-KDD model (Liu et al., 2018) was created, which is very important for understanding the relationship between data and knowledge. This model assumes that the data quality and previous knowledge are linked to creating new knowledge and affecting each step of the data processing process. Knowledge is not only the result of a process but it is also a prerequisite. Observations made by DQPK-KDD model will be used for designing a metamodel focused on the entire data flow.

Many companies depend on their employees' tacit knowledge (Shehzad et al., 2013). The same attitude is valid for the BI process itself (Shehzad et al., 2013). Broader synergies between the BI process and KM in the company should be used. KM helps one share knowledge in order to create new knowledge and provides BI with a better understanding of the business situation, thus allowing BI to predict results better and thus better evaluate the quality of acquired knowledge.

The KMBI framework (Cheng & Cheng, 2011) proposes integrating KM and BI in three layers:

data integration, functional/logical integration, and presentation integration. BI typically relies on structured and entity–relationship database data, while KM relies on unstructured data. They can be connected but somewhat indirectly. Shared services by KM and BI can be established – e.g. searching/querying or data storage. Shehzad et al. (2013) suggest that the BI and KM processes should remain separated but that interaction in all phases of each process should be allowed. The knowledge is used, for example, for the design of a data warehouse, in their mining and processing. A very intensive connection is recommended for the presentation (or user) layer. BI results should be combined with existing knowledge, and vice versa BI results should be stored as knowledge. It is interesting to note that prior knowledge is good for the content part of BI results and their presentation (Shehzad et al., 2013).

## Success Factors of BI Solutions

Success factors of BI solutions can be roughly divided into four areas: organisational (including human), process-related, technological and data-related. The content of categories has differed in the literature (details in Table 1). Technological and organisational factors remained, but other factors have changed over time. Human factors have changed in recent works, and the most recent research mentions knowledge and skills in this area (Surbakti et al., 2020). In older research, the motivation of employees and managers prevails. The change is also obvious in the perception of

**Table 1.** Critical factors of BI solutions. Source: Authors' enrichment of Hawking & Sellitto (2010)

| Author | Factors |
|---|---|
| Farley (1998) | Fast implementation, Ability to adjust to business requirements, Useful information, Ease of navigation |
| Watson & Haley (1998) | Management support, Adequate resources, Change management, Metadata management |
| Joshi & Curtis (1999) | Project-related factors (project plan must match with business demands and the scope of project management), Technical factors (DBMS selection, data loading, and efficiency of data access) |
| Sammon & Finnegan (2000) | Business-driven approach, Management support, Adequate resources including budgetary resources and skills, Data quality, Flexible enterprise model, Data stewardship, Strategy for automated data extraction methods/tools, Integration of data warehouse with existing systems, Hardware/software proof of concept |
| Wixom & Watson (2001) | Data quality, System quality, Management support, Adequate resources, User participation, Skilled project team |
| Little & Gibson (2003) | Management support, Enterprise approach, Prototyping data warehouse use, Metadata, Sound implementation methodology, External support (consultants) |
| Mukherjee & D'Souza (2003) | Data quality, Technology fit, Management support, Defined business objectives, User involvement, Change management |
| Yeoh & Koronios (2010) | Organisation: Management support, Clear vision and business case, Process: Business champion, Balanced team, Iterative development approach, Change management, Technology: Suitable technical framework, Data quality |
| Mungree et al. (2013) | Committed Management Support, Appropriate team skills, Flexible & appropriate technological framework, Align BI strategy with business objectives, Clean vision & well-defined system requirements, User-oriented change management, Effective data management, Committed and informed executive sponsor, Project scope management |
| Babazadeh sangar (2013) | Confirmation of Yeoh & Koronios (2010) + Project management, Training, Data quality management, IT systems management, User approach |
| Saltz & Shamshurin (2016) | Data (ability to store and access appropriate data), Governance (well-defined roles and responsibilities), Process (using a formal methodology such as Agile), Objectives (with measurable KPIs), Team (skills in data-driven decision-making), tools (to enable data-derived insights) |
| Villamarín & Diaz Pinzon (2017) | Directives and top management, Business linking, Champion, Business strategy, Change management, BI project deployment, People, Learning and Skills, Technology, Professional networks, Resources, Metrics, Environment |
| Surbakti et al. (2020) | Data quality, Data privacy and security and governance, Perceived organisational benefit, Process management, People aspects, IT: Systems, tools, and technologies, Organizational aspects |

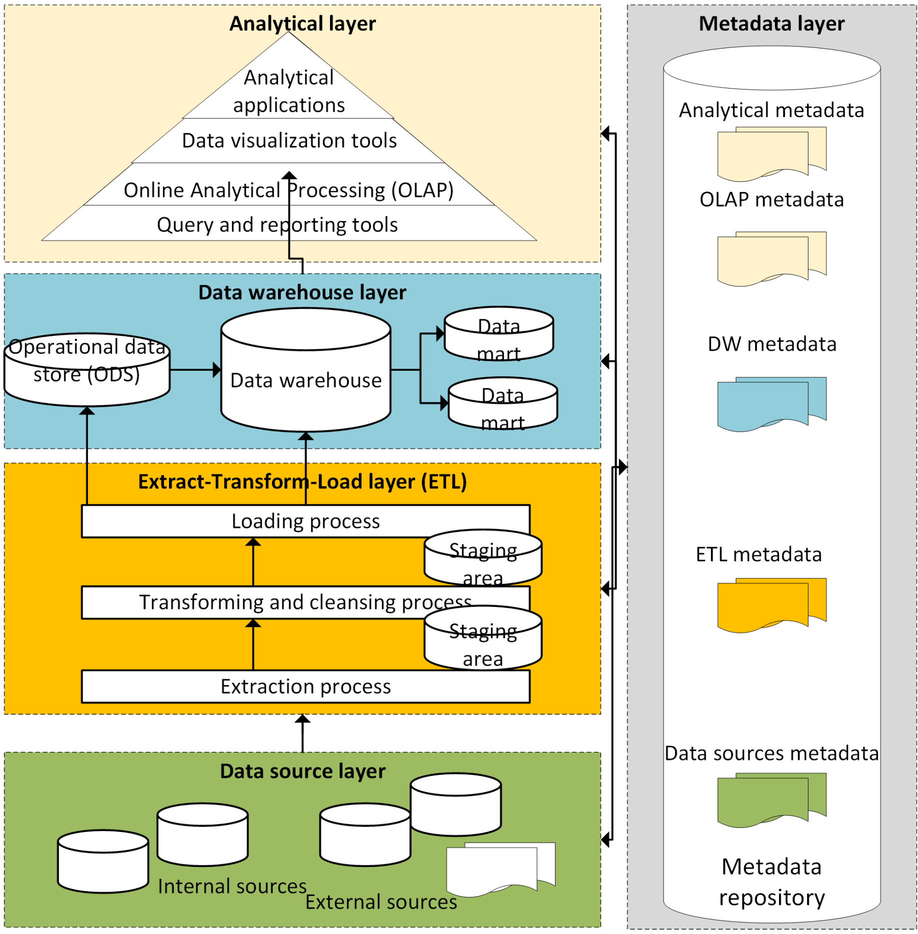


**Figure 2.** BI architecture with metadata layer. Sources: Authors, inspired by Ong et al. (2011)

data quality. The older approaches mainly refer to the quality of data connected with errors - garbage in-garbage out principle (Yeoh & Koronios, 2010). Recent research focuses on the information quality of data and emphasises its overall informative value (Surbakti et al., 2020).

The metamodel's creation is based on the general BI architecture (Ong et al., 2011) and the authors' own experience. At first, this mode was enriched by the metadata layer (Figure 2). This model basis will be extended by the knowledge layers (explicit and tacit).

## 4. Materials and Methods

Firstly, the creation of the new metamodel was based on the extension of the classical BI concept and secondly its practical value was based on feedback from business users.

A real business situation was selected to confirm the applicability of the metamodel. In relation to the author's personal experience, BI solution in the third biggest bank in the Czech Republic was chosen. Its BI solution is mature because it was established in 2008. It supports almost all business needs regarding analytics, reporting and modelling.

A simple questionnaire was prepared to survey people involved in this BI solution. The questionnaire contained eight questions: six closed questions and two open questions. The survey was performed during January 2021. Questionnaires were shared electronically via MS Forms to selected departments/employees. Responses were downloaded and processed in MS Excel software.

The questions used in the survey were the following:

1. Do you need descriptive data information/ knowledge for your work tasks?
2. How often do you need data knowledge?
3. What kind of data knowledge do you need?
4. What is the origin of this data knowledge?

5. How do you acquire the data knowledge?
6. Do you create new data knowledge in your work tasks?
7. Do you save created data knowledge?
8. Which is the knowledge repository that you use for your work tasks?

# 5. Results and Discussion

## Extension of Metadata About Existing Knowledge

The BI solution model's first extension extends the metadata layers by explicit knowledge connected to the data. These are common descriptions and explanations that relate to data collection, transmission, processing, and visualisation. Typical examples are shared methodologies, model documentation, extended glossaries, accounting methodologies or mapping methods. Examples of specific knowledge metadata are shown in Figure 3. Links between "classical" metadata and knowledge on data are essential for creating an environment where any useful information or knowledge is easily reachable.

## Use of Tacit Knowledge in BI

The BI architecture model's extension with a knowledge layer of tacit knowledge does not aim directly at creating a standard model including BI and complete KM. It emphasizes that BI also has a significant share in the tacit knowledge involved. If a company wants to increase BI solutions' effectiveness, specific people and their knowledge must be involved and actively used. Preserving and collecting this knowledge is a task related to KM, but BI should have access to this type of knowledge. For this reason, a synergy between BI and KM is required to enrich the context of productive and collaborative decision making in big organizations where multiple human and business entities continuously interact for the achievement of core business goals. At the same time, a new important piece is added into the big data V's (including among other concepts Volume, Velocity, Veracity, Variety and Value) (Moorthy et al, 2015) phenomenon via the tacit KM and metadata – based organizational "Value" creation.

Tacit knowledge is usually hard and expensive to share (Gubbins et al., 2012) or make explicit (Hansen et al., 1999). Also, motivation might be low because a limited group of employees uses

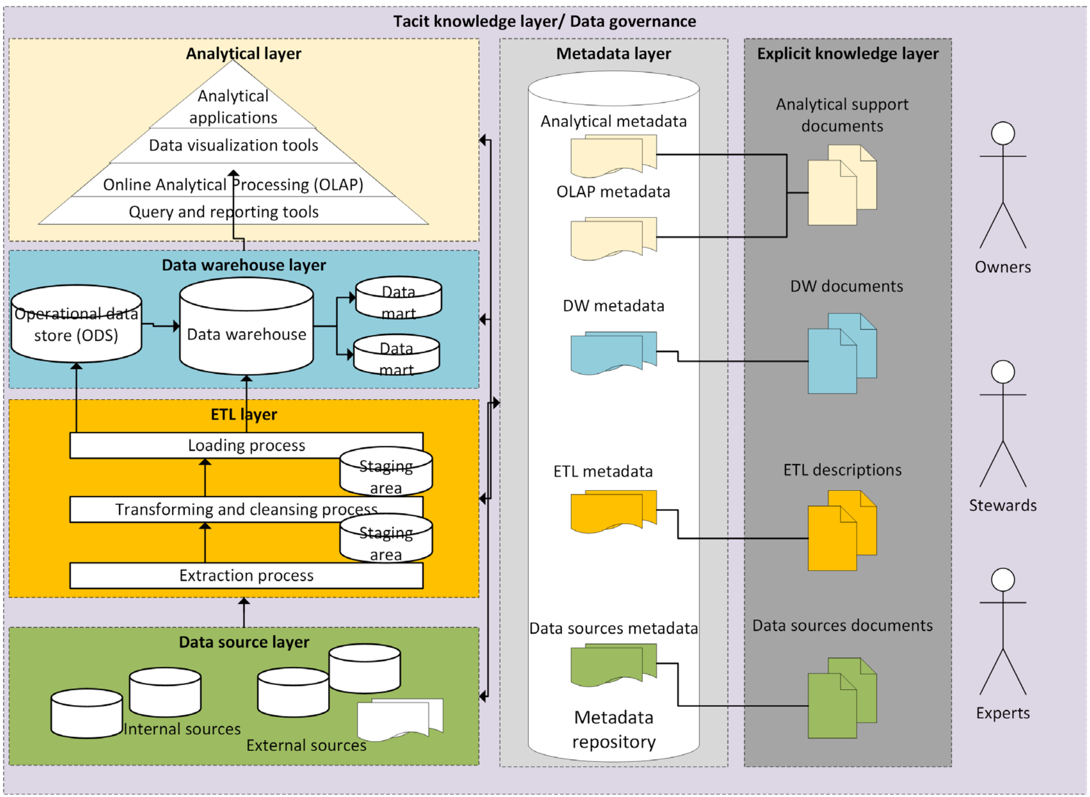


**Figure 3.** Extended architecture of BI solution with knowledge layers. Source: Authors

this specific knowledge, or such knowledge can be perceived as a personal advantage (Stenmark, 2000). There are two ways suggested for better access to tacit knowledge.

The first way is to create a data culture that motivates BI participants to share and demand knowledge. Creating a data culture is one of the success factors of a BI solution, and it is good not to forget any owner of the necessary knowledge when implementing it (Shehzad et al., 2013).

The second way is the consistent linking of data to the persons who participated in its acquisition, creation, transfer, or processing. It is one of the principles of data governance (DG). The DG enforces responsibility at the business owner's level, ensuring data management and data flows in their subordinate domain. There should also be a technical responsibility for implementing data flows and data transformations (Abraham et al., 2019). Linking to a specific person can also be done by linking through a specific role, which different people fulfil over time.

## Business Situation Application and Questionnaire Results

There were 22 participants across the BI solution. Most of them (7 participants) were from the data-science department. The second largest group (5 participants) was from the data warehouse operation department.

Detailed open questions (3 and 8) are not included as they do not carry value-added for external readers. Other results are mentioned in the text and illustrated in the graphs (for questions 1 and 7 in the text only).

The results showed that all (100%) the participants consider data knowledge to be necessary for their job tasks. Also, the need for data knowledge is quite frequent - for 63.6% of the participants, it is daily (Figure 4).

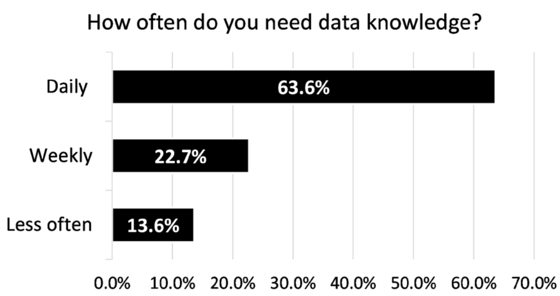


**Figure 4.** Frequency of data knowledge need.
Source: Authors

Additionally, 68.2 % of the participants showed (Figure 5) that they need data knowledge from more domains (business departments).

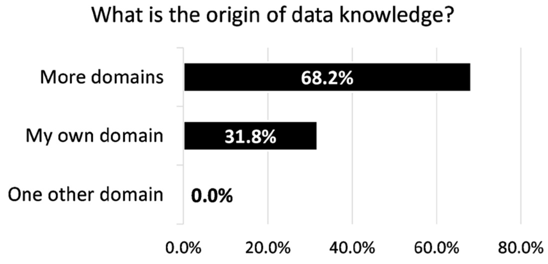


**Figure 5.** Origin of data knowledge.
Source: Authors

The mixture of ways how participants acquire knowledge suggests that tacit knowledge is a need or that there is a gap between stored explicit knowledge and real needs. Users/creators of this BI tool need tacit and explicit knowledge (Figure 6).

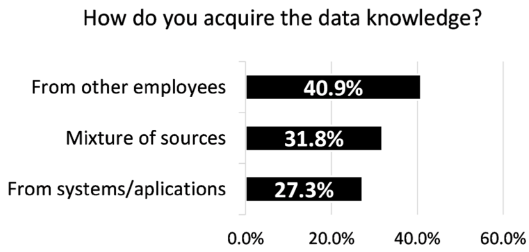


**Figure 6.** Ways of data knowledge acquisition.
Source: Authors

The survey participants also create new data knowledge - in 81.8% of cases (Figure 7). 55.6% of these data knowledge creators store their knowledge in dedicated places. Currently, there is no single explicit knowledge repository.

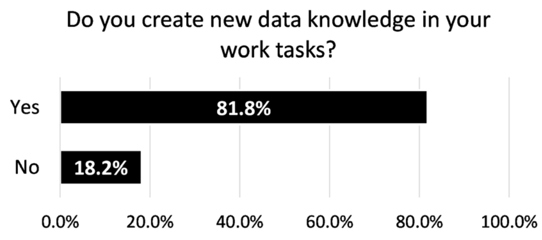


**Figure 7.** New data knowledge creation.
Source: Authors

## Comparison with Similar Studies

The need of data knowledge sharing was also confirmed in other studies. From a managerial point of view reliable, information-centralized knowledge bases have been found important;

since they allow further knowledge dissemination (Božič & Dimovski, 2019). The question on data knowledge need was raised in (McHenry, 2016). 75% of responding analysts express the need to verify validity and credibility of data with the business domains.

A general connection between several types of data knowledge and technical aspects of data quality was proved (Lee & Strong, 2003). If "why" data knowledge is provided to data collectors it leads to significantly higher data quality.

## Metamodel Enrichment

The case study confirmed that the knowledge layer is an inevitable part of BI solutions, and therefore, the metamodel proposed in this paper should be considered when developing new BI solutions.

Considering BI as a process, it is possible to show how the new metamodel impacts on information and knowledge flows. The process model concept was inspired by the theoretical model (Weiss, 2002), best practices (Hannah, 2019), and the authors' own experience. Traditional BI metamodels suggest data flows and information exchange take place in the metadata layer. The findings of this paper show that there are also intensive knowledge flows. The new metamodel suggests knowledge flow is an indivisible part of the BI process (Figure 8).

## 6. Conclusion

The pressure on business efficiency and innovation is high in the knowledge economy. BI solutions can provide useful knowledge, but their implementation alone may not be enough. Their functioning depends on many factors.

One of these factors is data quality. Data quality is defined according to several dimensions. One of these dimensions is the understanding of data. Data descriptions containing the meaning of data are essential for a good understanding of the data. Furthermore, knowledge, both explicit and tacit, is needed. Thus, a means to increase the effectiveness of a BI solution would be to increase data quality by improving data understanding.

The proposed contribution is based on the currently suggested BI architecture extension via an explicit knowledge metadata layer

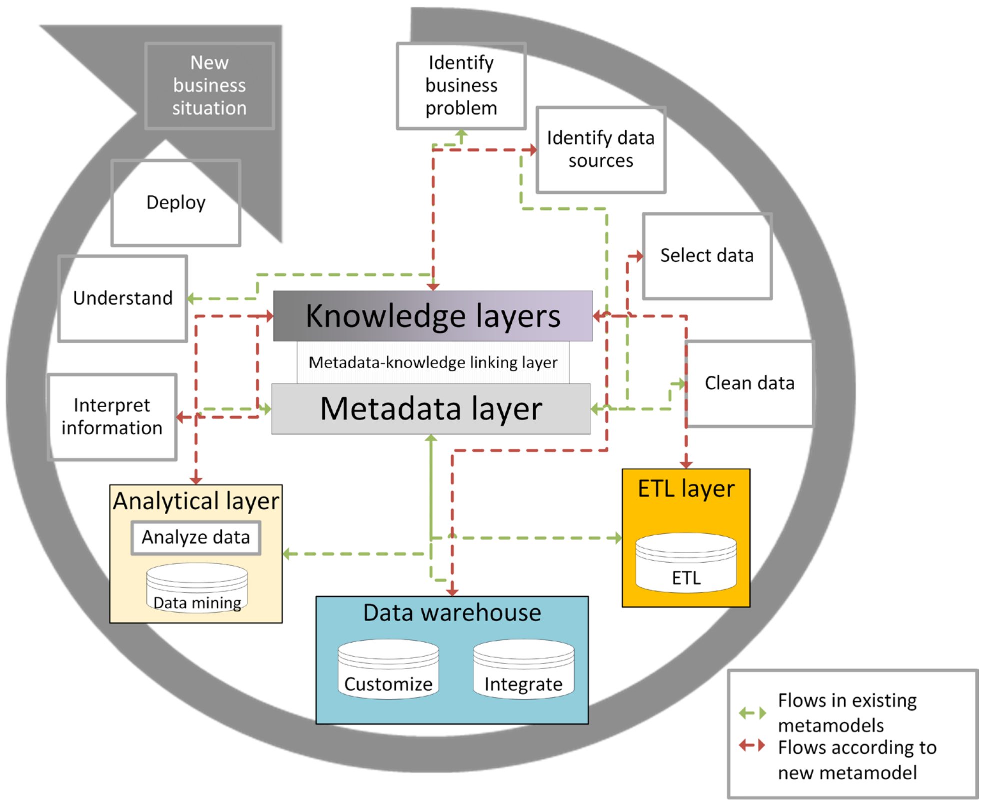


**Figure 8.** Business intelligence as process with information/knowledge flows. Source: Authors, inspired by Weiss (2002), Hannah (2019)

and a connection to a tacit "layer" via data/process ownership. The usefulness of the suggested metamodel is verified in the real business situation. The responses to the survey indicated that access to explicit and tacit metadata knowledge is crucial for efficient decision making and an improved BI performance. The connection of BI solutions to KM might be more complicated than previous frameworks suggested. An explicit knowledge layer can be created by enriching the data with more structured metadata. There are open questions regarding the implementation of the proposed model into practice. The structure of repositories covering structured metadata and relatively unstructured tacit knowledge should be investigated.

It is also recommended to introduce into BI the principles of data governance. If there is a clear ownership structure related to data objects, it should lead to higher tacit knowledge availability. The interesting question here is how to establish the environment in which business owners of data would understand technical aspects of data repository, transfers, and transformations. The metamodel should also reflect the broader environment in which BI was implemented as there might be factors and limitations coming from areas that have not been previously considered. Deeper integration of data usage and artificial intelligence suggests that future business success is related to working with complex data-technology-human systems. Moreover, business intelligence should be described as such a system.

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