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RESEARCH ARTICLE

Application of Semantic Web Techniques in DW/BI Systems for Strategic Management

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ABSTRACT Semantic Web techniques, such as ontologies, facilitate data and knowledge sharing in Information Systems due to their semantic formalization and inference qualities. Integrating knowledge-based artifacts into Decision Support Systems, such as Data Warehouse and Business Intelligence (DW/BI) systems, can provide new information sources, enable new analytical capabilities, and enhance decision-making. In previous work, the Balanced Scorecard Ontology (BSO) was developed to represent knowledge related to the Balanced Scorecard framework, including its concepts and relationships. The BSO was used to assess strategy formulation, implementation, and execution in a public sector organization, demonstrating its impact on strategy management. However, manual ontology population, especially related to performance indicator values, can lead to challenges in data availability, acquisition frequency, and quality. This paper proposes a semantic approach to integrating, aligning, and ensuring traceability between strategy and DW/BI systems. The Light Data Warehouse Ontology is introduced to represent the DW conceptual and logical models and semantically connect them with strategic information using the BSO. This integration enriches strategy analysis by providing strategic context to the BI environment and enabling automatic retrieval of performance indicator values. The proposed framework improves decision-making efficiency, reliability, and timeliness, providing managers with a data-driven environment aligned with organizational strategy.

INDEX TERMS Balanced scorecard, balanced scorecard ontology, data warehouse/business intelligence systems, semantic web, strategic management.

I. INTRODUCTION

Business Intelligence (BI) encompasses various applications, infrastructures, tools, and practices that enable decision-making through the access and analysis of data and information [1]. Data Warehouse/Business Intelligence (DW/BI) systems, which are data-driven Decision Support Systems (DSS), use an integrated repository of structured data (i.e., the DW) to provide analytical capabilities to decision-makers [2], [3]. Distinct DW architectures have been proposed [4], [5], with Kimball's data mart bus architecture and Inmon's Corporate Information Factory being the most widely recognized and used [6], [7]. In both of these approaches, DW/BI systems are designed to fulfill the analytical requirements of various organizational departments, ensuring a unified understanding of data, commonly referred to as a "single version of the truth" [8], [9]. Historical data is available as structured data within the DW

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to facilitate the extraction of Key Performance Indicators (KPI) and other relevant metrics tied to business processes and transactions (e.g., sales euro amount, sales quantity).

Although proficient in structured data analysis, traditional DW/BI systems encounter challenges when confronted with the growing diversity of unstructured data [10], [11], since they rely on structured data-focused query languages (e.g., SQL, MDX), which are inadequate for most Artificial Intelligence (AI) and Data Science analyses of unstructured data [12]. Organizations started to adopt new architectures, such as the Data Lake (DL) [13], [14], as their primary storage for structured and unstructured data. When integrated and organized, this data can be used to support Big Data, AI, or Data Science analyses. Several solutions are presented for integrating DW and DL architectures: i) the DL can be used as a data source for the DW; ii) the DW can be seen as part of the DL [10]; or iii) the DW and the DL can coexist in the same ecosystem, as they generally have different objectives and users (DW is mainly aimed at business users, while DL is aimed at data scientists) [15], [16].

Recently, the Data Lakehouse (DLH) [12] was introduced as the next generation of architectures [17], [18]. The DLH combines the flexible Big Data storage of the DL with the structured, clean, and integrated storage of DW to enable Data Science, Machine Learning, and BI analytics using structured and unstructured data. Nevertheless, business data produced by enterprise resource planning and operational systems remains mostly structured. For this reason, the importance of structured data (critical due to its representation of business transactions) and DW/BI techniques in dealing with this data is still paramount [10], even in the most recent architectures, such as the DLH and recent BI and Big Data architectures [14]. This paper focuses on DW/BI systems, with its main components being applicable independently of the architecture used, as long it includes a DW component.

DW/BI systems can be designed to support operational, tactical, and strategic decision-making processes [9]. At the strategic level, these systems should support strategic management, which consists of formulating, implementing, and evaluating strategies aimed at attaining long-term objectives and goals [19], [20]. Well-defined organizational vision and goals and BI & business strategy alignment were identified by Ain et al. [21] as important aspects for BI adoption, utilization, and success. The effectiveness of strategic management significantly impacts organizational performance in both public and private sectors, with the formalization of strategic processes shown to enhance performance outcomes [22]. However, most public organizations typically use strategic management systems with low comprehensiveness or formality and are usually decentralized [23]. Král [24] identifies research directions in this field, including continued performance evaluation, use of official quantitative data, and clear and understandable performance management systems (for policymakers, managers, and stakeholders).

In today's fast-paced business environment, organizations are often forced to continuously adapt to changes, which may lead to a misalignment between the planned and executed strategies [25]. This reinforces the need and relevance of establishing interoperability, traceability and monitoring capabilities between the strategy and organizational Information Systems (IS). Ontologies are used in the Semantic Web (SW) and other fields of study as a knowledge representation formalism, supporting interoperability by encoding data to facilitate sharing, reuse, and, more importantly, become machine-readable [26], [27].

Numerous challenges can be addressed by integrating ontologies into DW/BI systems and harnessing their semantic, formalization, and inference capabilities. These include resolving data heterogeneity and semantic issues, enhancing interoperability, streamlining integration processes, and providing semantic content for requirements and data analysis [28]. Establishing shared vocabularies across data and business domains is paramount for effective communication between business users and development teams and ensuring interoperability with other organizational systems [29]. This interoperability is essential for linking DW/BI systems with diverse data structures and architectures, facilitating the integration of structured and unstructured data within the same ecosystem or across architectures (e.g., between the DW and the DL) [28], [30].

The main objective of this research is to design and develop an integration framework to align strategic information with DW/BI systems by leveraging SW techniques, such as ontologies. This solution aims to support the integration, alignment, and traceability between strategy and DW/BI system, which are needed to provide data to monitor and evaluate strategic performance indicators. The improved interoperability between DW/BI systems and organizational strategy is critical to enable an automatic, accurate, traceable, and continuous evaluation of the strategy implementation, based on a data-driven approach [31]. Moreover, it facilitates the automatic validation of the strategy formulation, which can lead to adjustments in the BSC design. For instance, it enables the monitoring and testing of the cause-and-effect relationships of strategic objectives in the strategy map. If the data does not support a formulated cause-and-effect, then the design must be adjusted, formulating new strategic hypothesis.

Automating strategy evaluation, both in terms of its formalization and its implementation, and connecting it to data is critical since it promises enhanced efficiency, real-time insights, and the ability to handle the complexity of modern organizations [32]. In previous work [33], the Balanced Scorecard Ontology (BSO) was designed as a primary step in bridging the gap between strategic management and data related to Balanced Scorecard (BSC) framework [34]. Since its introduction in 1992, the BSC remains the most well-known approach for performance assessment due to the balance between non-financial and financial indicators across

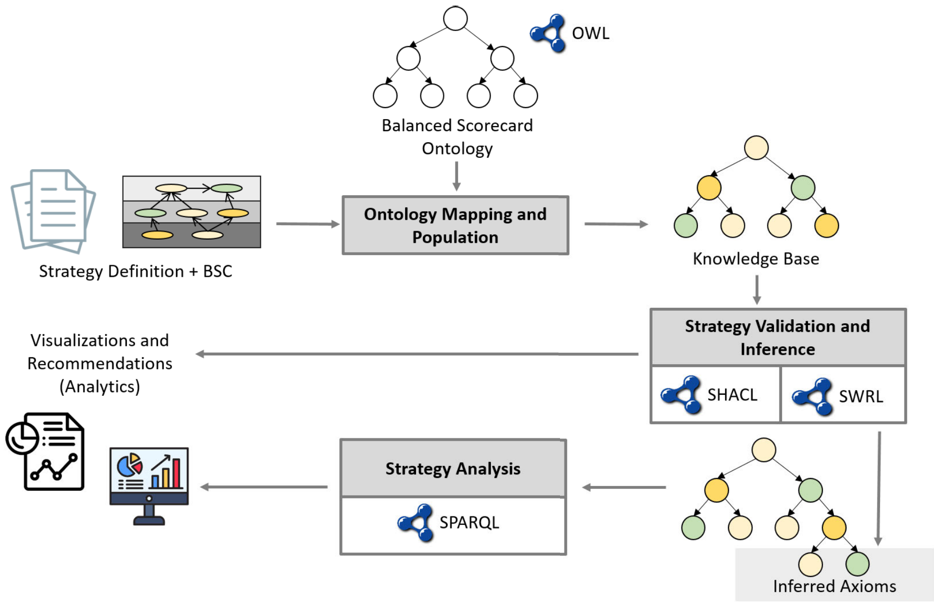

FIGURE 1. SW-based strategy analysis process used in previous work [38].

various perspectives [24], [35]. Although a simple and adaptable approach, the effective implementation of a BSC can be quite challenging. Manes-Rossi et al. [36] found that only 8% of the works in their literature review explore non-financial reporting from a strategic management perspective in the public sector. Moreover, existing studies, such as those by Kumar et al. [37] and Tawse and Tabesh [35], emphasize the importance of combining the BSC with other systems and tools for effective implementation. The BSO [33] provides a formal, structured, and semantically rich representation of the BSC framework, ensuring consistency in how strategic objectives, performance indicators, and their relationships are defined and interpreted, and providing decision-makers with a shared and unambiguous understanding of all BSC components. Furthermore, it provides a semantic layer to facilitate the integration, alignment, and traceability of strategic models with organizational IS.

To demonstrate the impact and potential of SW technologies in assessing strategy formulation, implementation, and execution, a public organization strategy was used as a case study in previous work [38], further exploring the impact of the BSO [33]. The solution used contained a semantic layer where the BSO was stored (using a graph repository) and a visualization and exploration layer, which used a traditional BI application to present strategic information. This work showcased the potential of ontology-driven strategic analysis to enhance organizational efficiency, adaptability, and decision-making capabilities while ensuring a shared understanding of strategies and performance data. The ontology was manually populated based on non-structured data sources, such as strategy documents and reports, using existing ontology population tools. Once populated, several SW technologies were used to validate and analyze both the strategy formulation and execution, as shown in Figure 1. Furthermore, visualization and exploration directly access the graph repository endpoint, requiring specific knowledge of the domain (e.g., ontology structure) and technology (e.g., query language).

Access to real-time data managed by organizational IS, such as the DW/BI system, is required to enable automatic and continuous monitoring and analysis of the strategy execution. However, establishing a seamless relationship between organizational IS data and strategy poses a significant challenge since performance indicators can be defined at different levels of detail. This paper proposes a semantic approach for the automatic integration of DW/BI system data into the strategy-domain ontology, addressing existing data accessibility challenges. This is vital to ensure the quality and consistency of ontological knowledge and the timely integration of performance data needed to support real-time decision-making regarding strategy execution. This paper presents the results and contributions developed in the context of a doctoral thesis [39].

The remainder of this paper is structured as follows: Section II presents the background and contributions of previous work, including a strategy-domain ontology, named Balanced Scorecard Ontology, followed by an in-depth analysis of the case study involving a public organization strategy and its analysis. From Section III onward, new contributions are presented and discussed. Section III introduces the proposed framework aimed at bridging the gap between strategy and data through the utilization of SW techniques. The Light Data Warehouse Ontology, is introduced in Section IV to represent the conceptual and logical DW models, followed by the description of API services designed to take advantage of this semantic solution in Section V. Section VI presents

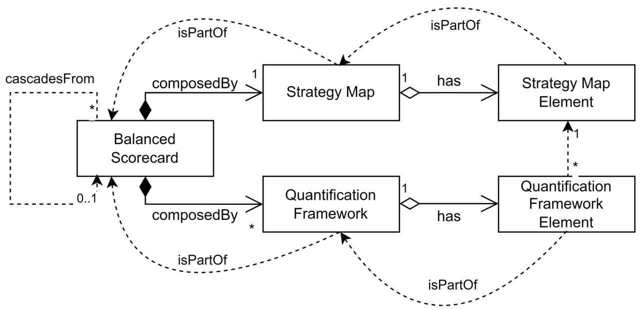

FIGURE 2. Balanced scorecard ontology concepts.

the process of linking data to strategy, demonstrating the impact of the proposed solution. Discussions, including contributions to practice and limitations and future work, are presented in Section VII. Finally, conclusions are presented in Section VIII.

II. BACKGROUND

This section presents the background work, namely the Balanced Scorecard Ontology and its application for strategic analysis in a public organization.

A. BALANCED SCORECARD ONTOLOGY

The Balanced Scorecard Ontology (BSO) was designed in previous work to bridge the gap between strategic management and data related to the BSC framework [33]. The BSO provides a structured framework to store and analyze knowledge related to the BSC, incorporating information about the strategic components and elements used for evaluating strategy execution. Specifically, the suggested formalization of the BSC framework provides a semantic layer to facilitate the integration, alignment, and traceability of strategic models with organizational IS, which are essential for supplying data to evaluate the BSC's performance indicators. Any organization can effectively formalize, communicate, align, and execute its BSC-based strategy by leveraging the BSO. Additionally, the ontology allows for strategy validation, such as ensuring each strategic objective is related to a BSC's perspective and evaluated by a performance indicator. It can also enhance interoperability between performance management systems and the strategy formulation process.

A BSC should be cascaded across various organizational levels, enabling managers to formulate and articulate strategies at corporate, departmental, team, and individual strategies (aligned with the employees' incentive systems). Within each department or organizational level, the information requirements vary, as does the granularity (or summarization) required to define and evaluate performance indicators effectively. Essentially, a BSC represents the aggregation of all cascading BSCs, starting from the corporate level and cascading down to the lowest organizational level.

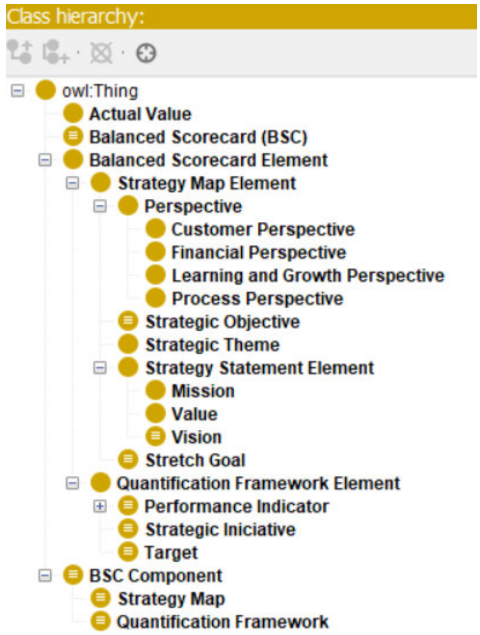

FIGURE 3. Balanced scorecard ontology class hierarchy.

FIGURE 4. The execution premium process. Adapted from kaplan and norton [31].

The BSO was developed in Protégé,[1] following the On-to-Knowledge methodology [40], to describe and store knowledge related to the BSC framework, including the strategy map and various quantification frameworks. These two essential components are required to define a BSC at any strategic level, as illustrated in Figure 2.

The Strategy Map offers a comprehensive view of the long-term strategy, including the following elements: strategy statement elements (i.e., vision, mission, and values), stretch goal, strategic objectives, perspectives, and strategic themes. On the other hand, Quantification Frameworks offer a shorter-term outlook, defining performance indicators, targets, and strategic initiatives required to implement and operationalize the strategy effectively (i.e., translate the

[1] https://protege.stanford.edu/)

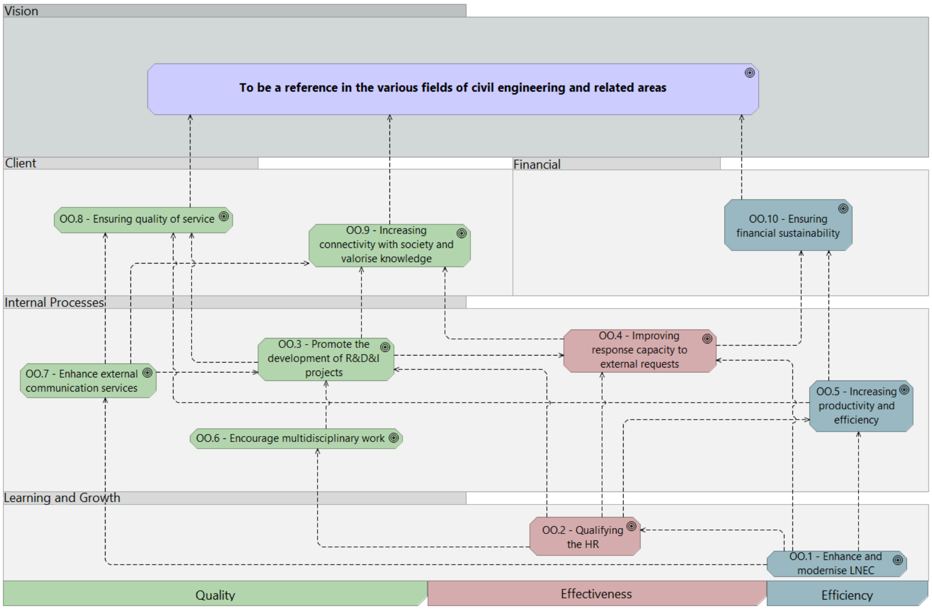

FIGURE 5. **LNEC's strategy map.**

strategy into operational terms). The BSO represents and formalizes these components and their elements, as depicted in Figure 3. Additionally, it captures the relationships between these elements and their attributes through object and data relationships, respectively. This formal representation facilitates analysis and inference regarding BSC elements and their relationships, including cause-effect relationships between strategic objectives. In addition to the BSC, its components, and elements, the BSO also contains information related to actual values of performance indicators, which store corresponding values related to a particular time frame, necessary to evaluate the strategy.

The BSO can be seen as an additional semantic layer seamlessly integrated into the Business Intelligence part of the Execution Premium Process [31], which proposes the key steps for effectively implementing a BSC (see Figure 4). In a comprehensive BSC implementation, the BSO facilitates the "Optimize Data" phase ("Monitor and Learn" and "Test and Adapt" processes), enabling accurate, traceable, and continuous monitoring and improvement of the strategy execution based on a data-driven approach.

B. CASE STUDY-LNEC

The Portuguese National Laboratory for Civil Engineering (LNEC) was established in 1946 to provide specialized services in civil engineering. As a public laboratory, it has been involved in national projects applied in multiple civil engineering domains (e.g., dams, communication routes, river and sea hydraulics, large structures) and international collaborations, performing scientific and technical works in almost fifty (50) countries. Over the years, LNEC expanded its competencies, becoming a hub for research, experimentation, postgraduate education, and community/local services.

As a public institute, LNEC has the legal responsibility to report on its activities and performance, ensuring alignment with strategic objectives. To this end, it publishes annual Activity Plans that report, among other things, on the evaluation of the objectives and indicators of the Evaluation and Accountability Framework[2] (QUAR). QUAR is a mandatory framework for assessing and monitoring the performance of Portuguese public organizations, ensuring alignment with strategic objectives and legal requirements while promoting transparency through public disclosure. QUAR includes various components such as the organization's strategic statements (mission and vision), strategic objectives, operational objectives, indicators, targets, and results achieved.

1) LNEC'S STRATEGIC ANALYSIS

A BSC approach was used to define the LNEC's strategy for 2021-2027, including the definition of strategic objectives and indicators used to monitor its execution [41]. Figure 5 illustrates the LNEC's strategy map. LNEC's strategy was used as a case study to analyze the impact and potential of semantic web technologies in the assessment of strategy formulation, implementation, and evaluation in public sector strategic management [38]. This previous work showcases the potential of ontology-driven strategic analysis to enhance organizational efficiency, adaptability, and decision-making capabilities, while ensuring a shared understanding of strategies and data. Ultimately, it offers a blueprint for public sector entities seeking to optimize their strategies (i.e., more informed, efficient, and impactful strategies), foster

[2] Article 10, Portuguese Law n. º66-B/2007, from 28th of December 2007.

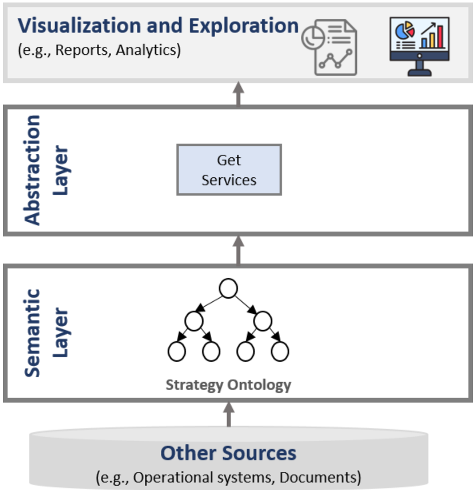

FIGURE 6. Solution used in previous work [38].

transparency, and deliver more effective services to the public they serve.

The BSO was used to store and validate the strategy formulation from LNEC. When complemented by semantic technologies such as SHACL[3] and SWRL,[4] BSO can be used to validate any set of rules and ensure that the ontology is consistent, and is structurally and data-wise compliant with the BSC model. The BSO can also be used to evaluate performance indicators, and monitor or validate cause-and-effect relationships between strategic objectives. Lastly, the BSO increases the interoperability of strategic information.

The populated ontology and the inferred axioms were imported to GraphDB,[5] a linked data environment compliant with W3C[6] standards (i.e., RDF, OWL, SPARQL). Once stored in this semantic graph database, the ontology can be queried or updated using SPARQL endpoints, allowing the ontology to be accessed by external applications. The initial approach at integrating strategic knowledge into the DW/BI environment directly imports information into the exploration environment (PowerBI[7]). GraphDB provides a REST API that allows, among other things, to query ontological repositories using SPARQL queries. Using this SPARQL query endpoint, strategy data can be directly imported into PowerBI datasets to be analyzed, by creating visualization and dashboards. This solution establishes a connection between the two platforms, as shown in Figure 6. However, it requires users to have a good understanding of the ontology (its entities, relationships, etc.) and the query language used to retrieve information, namely SPARQL, since GraphDB's API directly receives the query.

Figure 7 shows a simple dashboard obtained using this solution, displaying strategic information regarding the available LNEC indicators (reported in the annual QUAR). The dashboard allows the user to filter by quantification framework, presenting defined targets and actual values for each performance indicator.

Furthermore, data related to the evaluation of performance indicators was imported from non-structured data, namely the annual reports published by the public entity, involving a significant level of human intervention in the data extraction and ontology population process. Three significant problems arise from the existing approach: (1) The monitoring frequency of these indicators may not provide managers and decision-makers with timely insights to adapt to evolving business conditions; (2) The availability of data is limited to mandatory reported indicators, neglecting other important performance indicators that are currently not being evaluated by this solution; and, (3) Manual intervention is an error-prone process that can introduce data problems, impacting the quality of the decision-making process.

III. PROPOSED FRAMEWORK

The proposed solution for aligning the DW/BI system with the organizational strategy is presented in Figure 8. The Integration Framework takes advantage of SW technologies to formulate, validate, and ensure the effectiveness of strategies. Furthermore, SW technologies are used to materialize the relationship between strategic goals and DW data, providing a reliable source for data-driven insights necessary to enhance and support strategic management. The framework is comprised of a Semantic Layer and an Abstraction layer, ensured by API Services, a DSS (DW/BI system), and BI Applications.

The semantic layer contains a set of ontologies used to represent both the strategic knowledge and the DW structure. The BSO, introduced in [33], contains information about the strategy, formalized using a BSC approach, and provides a structured and machine-readable representation of the organizational goals, indicators, and targets. The Light Data Warehouse Ontology (see Section IV) is a new ontological artifact designed and developed to represent the DW's conceptual model, logical model and BI queries. This ontology allows users to define the measures and context of analysis related to organizational processes, and relate these entities to their logical representation, namely, fact tables, dimension tables, facts, and dimensional attributes. Also, it semantically represents BI queries used to gather data from the dimensional model. Lastly, a link set was defined to relate BSO entities to LDWOWL classes, presented in Section IV-D.

Upon storing the ontologies in a semantic graph database, users can query and update these knowledge bases through SPARQL endpoints. However, effective utilization of these endpoints requires BI users to possess a comprehensive understanding of SW techniques, such as ontologies, their entities and relationships, and the SPARQL query language as a prerequisite to access this knowledge. The development of abstraction layers, such as the Strategic Analysis

[3] https://www.w3.org/TR/shacl/
[4] https://www.w3.org/submissions/SWRL/
[5] https://graphdb.ontotext.com/
[6] https://www.w3.org/
[7] https://powerbi.microsoft.com/

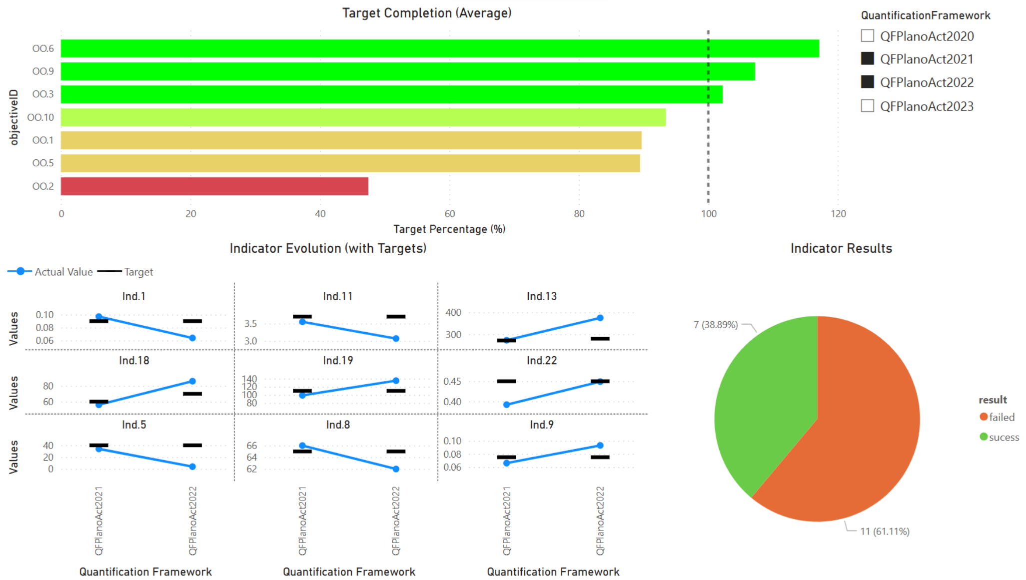

FIGURE 7. Strategy information in PowerBI.

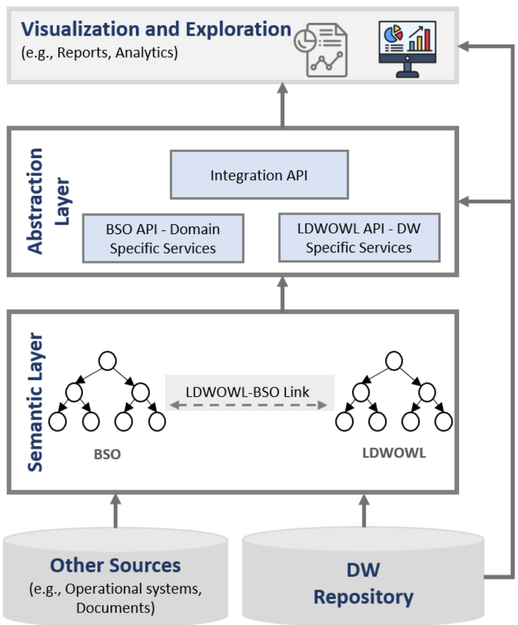

FIGURE 8. Integration framework.

Services, DW Analysis Services, and Integration Services APIs, was undertaken to enhance user interaction with ontologies, ensuring accessibility for users as well as external applications. The API was intentionally designed to facilitate future expansion and enhancement in response to evolving needs, providing flexibility for various services and use cases associated with the underlying ontologies.

As stated before, the DW is an integrated repository of structured data related to an organization. Typically, DW uses dimensional modeling to store data and provide simplified

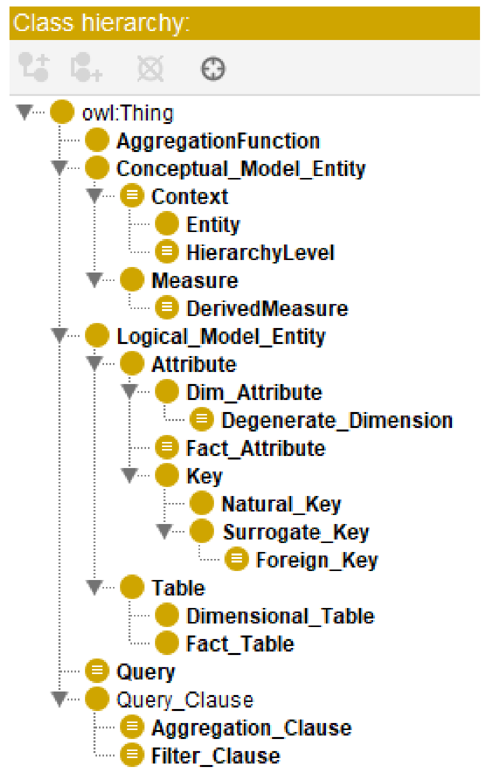

FIGURE 9. LDWOWL class hierarchy.

analytical and decision-support capabilities to business users, through BI applications [9], [29]. The Integration Framework enables managers and decision-makers to validate and analyze their strategies based on ontological knowledge and SW technologies supported by DW data. BI applications

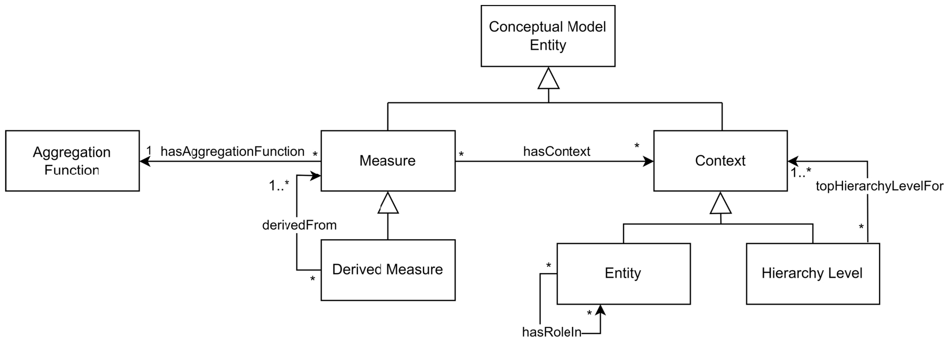

FIGURE 10. LDWOWL conceptual model entities.

can benefit from ontology knowledge to provide end-users with strategic information. By using visualizations and recommendations regarding strategies and their executions, these applications can help managers validate the formulated strategies, evaluate performance indicators, and validate cause-and-effect relationships between strategic objectives. This fully integrated solution allows managers to interact, monitor, analyze, and receive alerts or even analytical recommendations regarding their strategy implementation and evaluation.

IV. LDWOWL

The Light Data Warehouse Ontology (LDWOWL) was developed as a means to semantically connect DW systems to other domains (such as BSO's strategy). The ontology was developed in Protégé to support the DW requirements and star-schema analysis. LDWOWL entities (see Figure 9) are used to represent a DW's conceptual model, logical model, and BI queries.

Following established database modeling practices, the conceptual model provides a high-level abstraction that captures the main entities, attributes and relationships in a domain. This model is designed to communicate the intended content and structure of the domain to both technical and non-technical stakeholders. In contrast, the logical model provides a more formal and structured representation, adapted to a specific data storage paradigm, as for instance, the relational model.

As outlined in [28], ontologies are currently being used during the dimensional modeling process to streamline dimensional design, discover business entities and their relationships, and find potential facts and dimensions from each data source. Consequently, much of the existing literature positions ontologies either as the primary resource for the DW or as an intermediary layer between the source system and the ETL process. However, there is an absence of ontologies capable of conceptually formalizing dimensional models. While ontologies effectively capture business/domain-specific entities and their relationships (e.g., Client, Sale), they overlook the fundamental concepts that form the basis of dimensional models (e.g., Dimension table, Fact table). Recognizing this gap, the LDWOWL was designed and developed to contribute to this particular challenge, aiming to semantically integrate DW with other domains, such as strategy (e.g., formalized in BSO).

A. CONCEPTUAL MODEL

Business requirements definition is a pivotal part of the design of a DW/BI system [29]. The elicitation of business concepts is key during this process, where business users and DW/BI experts are tasked with identifying and classifying business entities as either context (dimensions) or measures (facts). Process-driven DW design methodologies, such as BEAM - Business Event Analysis & Modelling [42], focus on identifying business events within the organization and describing them. Methods, such as the BI Model Canvas [42], are used to collect event information related to products/services (*What*), time (*When*), places (*Where*), persons/organizations (*Who*), motivations (*Why*), or process information (*How*). In addition to the event context, measures (*How many*) are also identified, allowing event performance to be measured. The resulting conceptual model can now be stored in the LDWOWL (see Figure 10).

As stated before, in a DW/BI system, concepts can be either measures or context. Measures are indicators, such as quantities, currency, or amounts of time, measured during the execution of events. Since the individual value of each transaction is not of analytical interest, these values should be aggregated into measures. The same value can be used for multiple measures, depending on the aggregation function used. For example, in a sales context, Total Sales Value and Average Sales Value are two different conceptual measures that are obtained by applying different aggregation functions (in this case, sum and average) to the same measure (Sales Value). Measures can also be derived to obtain Derived Measures (e.g., ratios), and can be classified according to their additivity (additive, semi-additive, or non-additive).

Measures are aggregated according to a given context. Users can use the "hasContext" object property from LDWOWL to evaluate the analytical context of each measure, which can be further specified following BEAM's 7W's (e.g., the "*When*" information can be associated with a

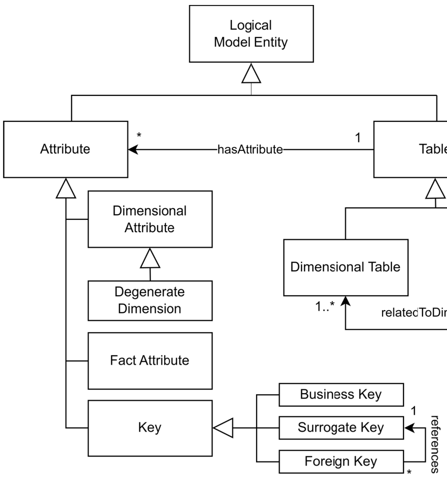

FIGURE 11. **LDWOWL logical model entities.**

measure using the "hasTemporalContext" object property). Furthermore, context typically exhibits well-defined hierarchical relationships, which are used within DW/BI systems to construct aggregate or derived models and guide model exploration within BI applications. In LDWOWL, these top-down hierarchies between contexts are defined using "bottomHierarchyLevelFor" and "topHierarchyLevelFor" (e.g., $< Month >$ topHierarchyLevelFor $< Day >$), also ensuring the conformity between these. Moreover, LDWOWL can take advantage of other Semantic Web standards, such as SWRL, to add inference rules such as the one presented below:

$$Measure(m) \wedge hasContext(m, c_1) \wedge$$
$$bottomHierarchyLevelFor(c_1, c_2) \rightarrow hasContext(m, c_2)$$

This rule allows the ontology to infer relationships between measures and hierarchy levels based on the asserted relationships between measures and base context (or lower hierarchy levels). Base context, such as Day, Location, Client or Collaborator is stored as "Entity". However, an Entity can be used as a Hierarchical level of one or more entities (e.g., Location can be used to aggregate clients or collaborators).

B. LOGICAL MODEL

The logical model of a star schema represents how the data will be stored and organized within the DW, as shown in Figure 11. The metadata of these models can be stored within LDWOWL, allowing them to be associated with and validated against the conceptual model.

Dimension Tables represent context information about analytical-relevant business entities (e.g., Day, Client). Entities with an explicit hierarchical relationship are usually represented within the same table (e.g., Product, Model, and Brand are represented within the Product dimension table). In addition to the dimensional attributes (used to aggregate and filter facts), dimensional tables have a surrogate key (primary key) and can contain several business keys (which identify a business entity and its records in the source systems). Facts are stored in the center of the star schema, called the Fact Table. Facts are typically numeric values representing measurable and quantitative data. The fact table also contains foreign keys for each of the associated dimensional tables, and may contain degenerated dimensions (context information stored in the fact table, such as transaction identifiers).

Figure 12 presents the high level relationships between conceptual and logical entities in LDWOWL. Concepts must be related to an attribute using the "hasLogicalAttribute" object property, ensuring that they are represented in the DW. Measures are related to fact attributes from the logical model,[8] while context information is related to dimensional attributes. Furthermore, a default aggregation attribute (a sub-property of the "hasLogicalAttribute" object property) can be defined as a for each context concept (e.g., "Stock Keeping Unit (SKU)" for Product, "Brand name" or "Brand Code" for Brand), allowing users to aggregate by a certain context without specifying a desired attribute.

C. BI QUERIES

Most queries against a star schema follow a consistent pattern, requesting facts summarized by dimensional attributes that provide context and act as filters to restrict the data retrieved and aggregated. This common approach is known as a standard or typical BI query [9], [43].

A Query concept can also be stored within the LDWOWL, following the typical BI query SQL pattern, as shown in Figure 13. A BI Query focuses on a measure ("queriesMeasure"), which is typically aggregated using an SQL aggregation function (e.g., "SUM", "COUNT", "AVG"). The query defines how this measure should be:

(a) aggregated over some context ("aggregateBYContext"), leading to a GROUP BY clause in SQL;
(b) filtered for some context ("filterFORContext"), leading to a WHERE clause in SQL.

The ontology defines how a certain measure is analyzed, relating the measure with a set of context entities (at any hierarchical level), and providing knowledge related to the representation of these concepts in the DW's conceptual model. Filter clauses support the definition of filter values, allowing the storage of filter information (such as "equal to" or "greater than" a certain value) in a formal way (as shown in Figure 14). The query is related to a measure ("Total Expenditure"), which is aggregated by a context ("Month") and filtered by a second context ("Funding Category"). The filter is defined using the "equalTo" data property, which, in this case, filters the measure for "Grants" (i.e., Funding Category = "Grants").

[8] If avoidable, non-additive measures (such as ratios) should not be represented in a fact table. The fact table should, instead, store the additive measures that are used to calculate these derived measures.

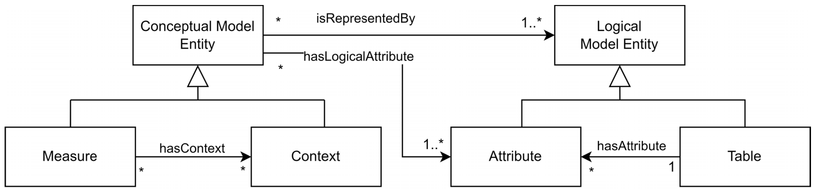

FIGURE 12. LDWOWL relationships between entities in the conceptual and logical model.

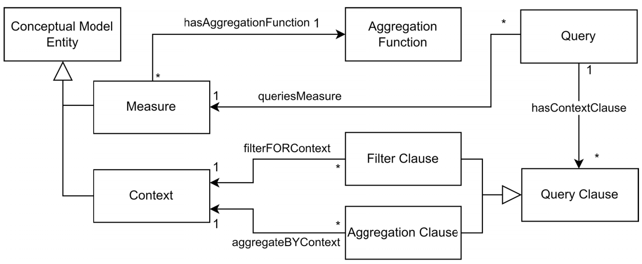

FIGURE 13. LDWOWL BI query entities.

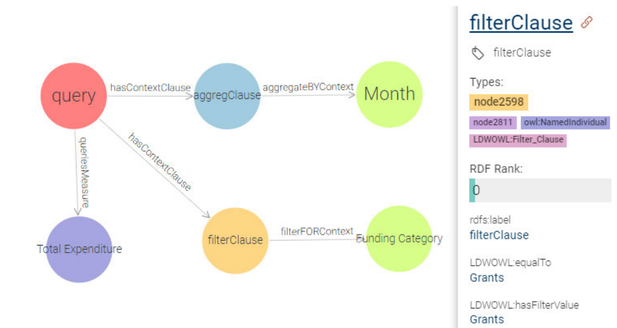

FIGURE 14. LDWOWL query example (GraphDB visualization).

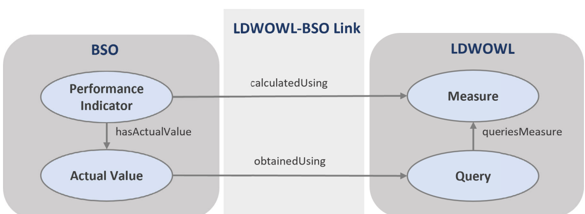

FIGURE 15. LDWOWL - BSO link.

D. THE LDWOWL-BSO LINK

As previously mentioned, the LDWOWL was developed as a means to semantically connect the DW to other domains, namely with the BSO's strategy. The LDWOWL - BSO link set was developed to link these two ontologies, defining the object properties needed to relate BSO entities to LDWOWL entities, effectively linking strategy to the DW, as shown in Figure 15.

The LDWOWL's Measure and Query entities serve as anchor points between the BSO and the DW information. The "calculatedUsing" object property relates performance indicators to conceptual measures. These measures are represented in the DW through facts (which can be directly available in transaction fact tables or be made available by designing derived tables, such as periodic snapshots). This measure can then be analyzed according to a certain context defined in the conceptual model.

An actual value related to the execution of a performance indicator can now be connected to an LDWOWL Query by using the "obtained using" object relationship. The query defines the context needed to aggregate and filter a measure, allowing it to explicitly define how a certain value for a performance indicator should be calculated, regardless of its detail level. This enables users to formally detail and retrieve the necessary data to evaluate their strategy, without the knowledge and complexity of the logical model.

V. ONTOLOGY ACCESS

Once stored in a semantic graph database, such as GraphDB, ontologies can be queried or updated using SPARQL endpoints, allowing the BSO and LDWOWL ontologies to be accessed by external applications. However, access to the SPARQL endpoint requires BI users to have a good understanding of the ontology (its entities, relationships, etc.) and the query language used to retrieve information, namely SPARQL. Both the BSO and the LDWOWL REST API services were developed to provide an abstraction layer for users to interact with the ontologies (see Section III). These services were developed in Python using FastAPI[9] and SPARQLWrapper.[10] They do not encompass an exhaustive list of services or use cases associated with the underlying ontologies, being intentionally developed to allow them to be expanded and improved as necessary.

A. BSO API

The BSO services were based on the competency questions initially defined in its Ontology Requirements Specification Document, presented in [33] and use cases developed for strategy analysis, namely those presented in [38]. Table 1 presents a summary of currently available API services related to the BSO.

B. LDWOWL API

Similarly to the BSO API, a set of services was developed to access and update knowledge related to the LDWOWL.

[9]https://fastapi.tiangolo.com/
[10]https://sparqlwrapper.readthedocs.io/

TABLE 1. BSO API services.

Services	Description
BSO - Balanced Scorecard	Services related to the BSC class. Allows to obtain a list of existing BSCs from the ontology, information related to them, such as strategy elements (Mission, values and vision), time-horizon and organizational level, and their components (strategy map and quantification frameworks);
BSO - Strategy Map	Services related to the strategy map. Contains endpoints to get information concerning strategic objectives, perspectives (and their order) and strategic themes pertaining to a strategy map;
BSO - Strategic Objective	These services allow the individual analysis of strategic objectives. Given a strategic objective, information related to the objective perspective, strategy themes and performance indicators can be obtained. A list of objectives influenced directly or indirectly by cause-and-effect relationships can also be retrieved;
BSO - Performance Indicator	Services related to a performance indicator, namely the type (lead or lag), properties (e.g., data acquisition frequency), and defined targets;
BSO - Strategy Execution	Services related to actual values of performance indicators (including the addition of new values) and initiatives
BSO - Cascading	Services related to BSC cascading (how BSCs and strategic objectives are related across organizational levels)
BSO - Strategy Analysis	Currently, two different services are provided, related to use cases developed for LNEC's strategy analysis. First, given a quantification framework, a complete overview is provided, detailing strategy objectives, performance indicators, related targets, and actual values, allowing users to evaluate the strategy performance. Second, a comparison between frameworks, which is useful for validating cause-and-effect relationships, as shown in [38].

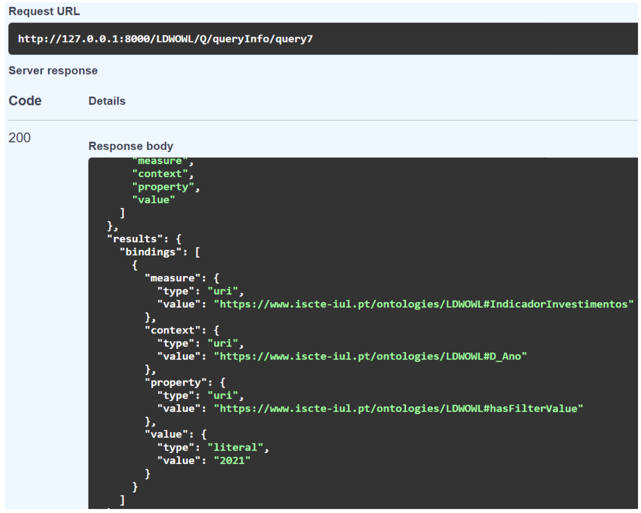

FIGURE 16. Query measure and context information from LDWOWL API.

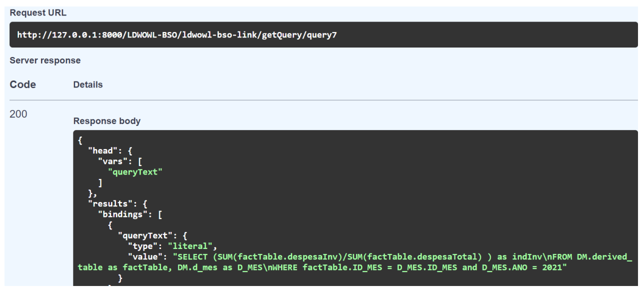

FIGURE 17. Resulting SQL query from LDWOWL API.

These services include obtaining the measure context, the aggregation (hierarchical) paths for context and the available attributes for a given context. Furthermore, the API allows the retrieval of existing queries, query context (aggregation and filter context), and the default attributes necessary to run the query (and ensure that they are connected in the logical model, i.e., that the fact table with the necessary fact is related to the context's dimensions).

Moreover, the service allows the transformation of BI queries to their respective SQL queries, which then allows the DW to be queried and data to be retrieved. The logical model stored within the LDWOWL is used to fill in information regarding tables and surrogate keys, as well as the necessary fact and dimensional attributes. The transformation of the Query concept in LDWOWL (see Section IV-C) into SQL query text is supported by the BI query pattern, which guides the translation of each query-related concept into SQL as follows:

- Measure: The measure specified in the query determines the corresponding fact to be retrieved. The SELECT clause is constructed using this fact along with the appropriate aggregation function, and the measure name is used as an alias. The associated fact table is included in the FROM clause;
- Context from Filter Clause: The relevant dimensional attribute is used as a filter by adding it to the WHERE clause, along with the corresponding filter value and based on the specified data property (e.g., "equalsTo" results in "="). The associated dimensional table is included in the FROM clause (if not already present), and an inner join is ensured by comparing surrogate keys in the WHERE clause;
- Context from Aggregation Clause: The relevant dimensional attribute is used to aggregate the fact by being included in the GROUP BY clause. The corresponding dimensional table is added to the FROM clause (if not already present), and an inner join is ensured by comparing surrogate keys in the WHERE clause. The attribute is also included in the SELECT clause to provide the aggregation detail in the query result.

However, this method is currently limited, only working with single fact queries and assuming filter clauses to always be in conjunction, as it relies on the typical BI query pattern. Queries with multiple facts or derived measures can be stored

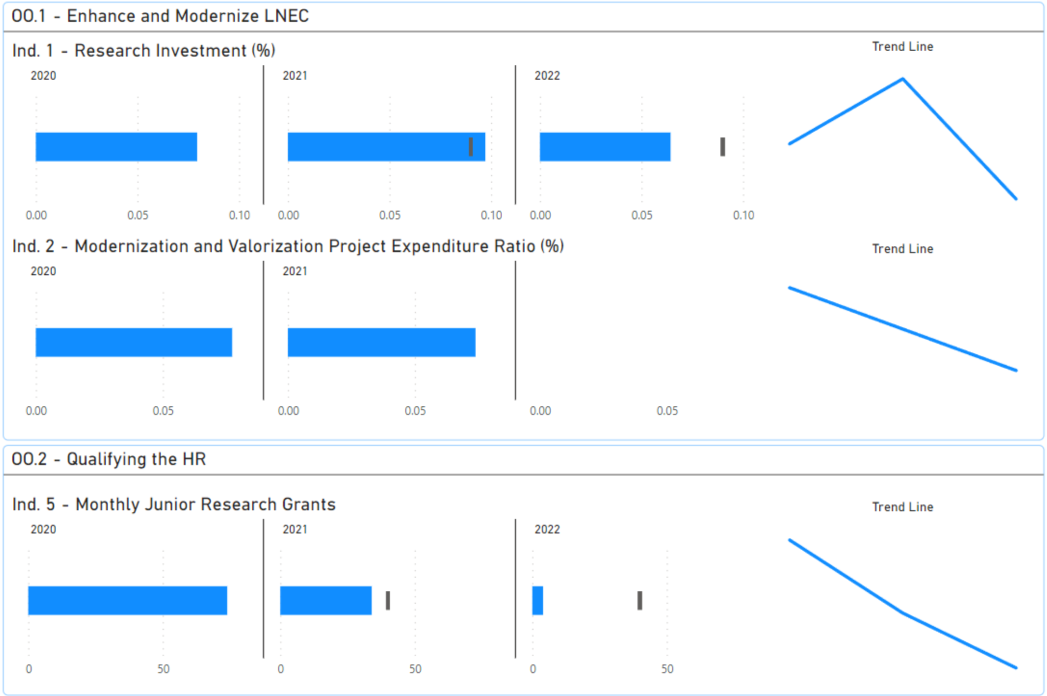

FIGURE 18. PowerBI Visualization: OO.1 and OO.2 evaluation.

in the ontology, however, their SQL query text must currently be stored and obtained using the "rdfs:comment" annotation.

Figure 16 presents the query information, including measure and context information, resulting from a GET service from this API, shown in Swagger.[11] The specific query uses the year context ("D_Ano") to filter the investment indicator ("IndicadorInvestimentos", in Portuguese) for the year of 2021. Another service can be used to obtain the SQL query text, as illustrated in Figure 17. The investment indicator for 2021 is calculated by dividing two facts from a derived table, filtered by the month dimension for the year in question.

C. INTEGRATION API

A set of services was developed to take advantage of the LDWOWL—BSO link and showcase the integration between the DW/BI and the BSO's strategy. These services are designed to validate this integration and enable effective strategy execution and decision-making by automating the ontology population process.

The first set of services enabled by the LDWOWL - BSO link concerns the validation of strategy/data alignment. By taking advantage of this integration, users can validate if all of the performance indicators are connected to conceptual measures or if the queries for retrieval of their actual values are formalized in the ontology. Furthermore, since the conceptual and logical models are related in the LDWOWL, these queries can be validated against the ontology. This ensures that the necessary facts exist, that they can be computed at the required level of detail (with the appropriate hierarchy levels in the related dimensions), and that they can be filtered by existing dimension attributes.

The second set of services showcases how this solution can be used to enable the automatic extraction of the values of performance indicators from the DW and populate them into the ontology. Given a BSO performance indicator, BI queries are obtained from the LDWOWL for any missing actual value related to that performance indicator. These BI queries are then transformed into SQL queries and used to retrieve data from the DW, which, in turn, is used to populate the BSO. A similar service can also be used to validate existing actual values already in the ontology. As shown in Section V-A, the BSO API provides strategy analysis services that take advantage of this new information retrieved from the DW. By using DW/BI system data, this approach enables reliable and data-driven strategic decision support for users and managers.

VI. LINKING DATA TO STRATEGY

The Integration Framework, as proposed in Section III, aims at aligning the DW/BI system with the organizational strategy, by taking advantage of SW techniques, such as ontologies. LNEC's case study, presented in Section II-B1, was used to demonstrate the integration framework, which allows the retrieval of performance indicators' actual values from the DW into the BSO, due to the semantic integration between the LDWOWL and BSO. The application of

[11] https://swagger.io/

this framework in our research is supported by two key prerequisites, both of which have already been met:

1) The organization has already developed a Data Warehouse. The framework operates on the premise that the DW was designed following a dimensional modeling approach and contains all the necessary data for evaluating organizational performance.
2) The organizational strategy was formulated using a BSC and is formalized using the BSO. As stated before, the case study's strategy was already populated into the BSO, which enabled a set of semantic-based analyses related to the validation of the strategy formulation and evaluation of organization performance, as shown in [38].

To demonstrate the integration framework, data regarding the evaluation of Ind. 2 - Modernization and Valorization Project Expenditure Ratio (%) was automatically retrieved from the DW and populated into the BSO knowledge base containing LNEC's strategy. As indicated in previous work (see Section II-B1), data on indicators whose reporting is not mandatory (i.e., are not reported in QUAR), such as Ind. 2, was unavailable.

The actual values of the performance indicators are now retrieved via the Integration API service, which identifies the necessary BI queries related to that indicator, obtains the actual values from the DW and fills in the ontology with those values. This service was used to obtain data relating to a performance indicator with missing monitoring information. Among other capabilities, this solution can be used to automatically validate existing ontological knowledge with data from the DW and obtain performance evaluation data more frequently.

Once this information is contained in the ontology, external applications, such as BI applications, can take advantage of the existing APIs to create reports and visualizations and execute data-driven analyses related to organizational strategy. Figure 18 shows a simple visualization regarding the evaluation of two strategic objectives from LNEC's strategy, together with their respective performance indicators, including Ind. 1 and Ind. 2 for the strategic objective OO.1 - Enhance and Modernize LNEC, and Ind. 5 for strategic objective OO.2 - Qualifying the HR.[12] Furthermore, the visualization also presents targets and trend lines for each performance indicator. With sufficient data from the DW, this approach can be used to automatically obtain data on all performance indicators, enabling LNEC's strategy to be fully evaluated and analyzed at any required frequency.

However, it's important to note that in Figure 18, Ind.2 lacks defined targets as they were not defined in the LNEC strategy documents, and consequently were not populated into the BSO during the research described in [38]. In this case, the strategy evaluation process is hindered without the correct formalization of the strategy and its performance indicators, which could be ensured by the BSO. Indeed, one of the key advantages of using the BSO and its related API services is the ability to identify this type of weaknesses in strategy formulation.

Managers and decision-makers can leverage these formalisms to enhance their analysis and exploration by providing additional context and knowledge within the BI environment. When integrated with real-time data managed by organizational IS, strategic information, including targets, initiatives, and cause-and-effect relationships of strategic objectives, plays a pivotal role in supporting data-driven decision-making, ensuring a reliable and effective strategy execution.

[12]More information related to these performance indicators and strategic objectives can be found in [38], Section VII - Strategy Analysis.

VII. DISCUSSION

This paper explores the application of SW technologies in DW/BI systems for strategy analysis and management. In previous research, the BSO was used to validate and infer over strategic knowledge of a public organization. Reference [38] explored how organizations can employ these techniques to assess their strategy formulation and execution. The BSO was used to evaluate performance indicators and validate the cause-and-effect relationships between strategic objectives while ensuring a more reliable and accurate representation of the BSC framework (i.e., ensuring that the organization's strategy formulation is semantically, structurally, and data-wise compliant with the BSO model).

However, ontology-based strategy evaluation and analysis can be hindered by a lack of data. Access to actual data managed by organizational systems, such as DW/BI systems, is essential to provide a reliable base for strategy evaluation and analysis. Furthermore, establishing a seamless relationship between this data, encompassing values collected for each performance indicator, and their ontological representation (in the BSO) is an intricate and complex challenge to which this research contributes. An Integration Framework is proposed for aligning a DW/BI system with the organization strategy (see Section III), by using SW technologies to materialize the relationship between strategic entities and DW data. By establishing this relationship, the process of extracting values from IS and integrating them into the ontology can now be automated, providing a reliable source for data-driven insights necessary to enhance and support strategic management. By bridging the gap between data and strategy, organizations can enhance their ability to monitor and analyze strategy execution accurately, thus facilitating more informed decision-making processes.

A. CONTRIBUTIONS TO THE PRACTICE

The alignment of IS, namely DW/BI systems, with strategic knowledge can augment previously identified advantages that the BSO and SW technologies offer to managers and decision-makers. First, formulating a strategy, particularly the cause-and-effect relationships from the BSC framework, often depends on managers' insights, knowledge, and intuition. The proposed framework facilitates the integration of performance data into the BSO, enabling the monitoring and empirical validation of these relationships. This proactive approach prevents decisions that may not contribute to the organization's long-term success, preventing the misallocation of resources to the fulfillment of non-essential or redundant strategic indicators and objectives. Furthermore, by using actual data related to strategic execution, the proposed solution can enable dependency analysis processes, providing insights into how changes in a specific indicator or objective may impact the overall strategy.

Second, the use of ontologies, such as BSO and the LDWOWL, provides increased interoperability, enabling the sharing of information and data across systems and organizations. This interoperability is key in an integrated solution such as the one proposed in this research, making the collection, analysis, and reporting of performance indicators more efficient. The automation of data integration from organizational IS is crucial for supporting real-time or near-real-time monitoring of performance indicators and data-driven decision support.

Finally, industry, government, and university organizations around the world often need to adhere to regulatory requirements and comply with relevant standards, such as those established by policymakers (e.g., the European Commission). SW technologies can play a crucial role in supporting compliance and governance initiatives by enhancing external communication and alignment, by leveraging their semantic interoperability to streamline documentation and reporting. For example, public organizations in Portugal, such as LNEC, are subject to a mandatory framework for assessing and monitoring the performance of Portuguese public services. The proposed solution can facilitate the automatic evaluation and reporting of indicators for compliance frameworks. Furthermore, due to the semantic integration between the BSO and LDWOWL (see Section IV-D), managers can define BI queries to answer each performance indicator, enabling the report and analysis of all performance indicators related to the organizational strategy. By using LDWOWL's DW conceptual model, the proposed integration framework facilitates the formulation of BI queries, ensuring and validating that each performance indicator can be evaluated.

B. LIMITATIONS AND FUTURE WORK

This research and previous work [33], [38] showed how ontologies and SW technologies can provide external applications and end-users with strategic information, and enable strategy validation and analysis for managers and decision-makers. However, additional work is required to fully showcase the potential of these technologies as part of a fully integrated BI solution, where managers can interact, monitor, analyze, and receive alerts or analytical recommendations, regarding the execution of the strategy. Additionally, such solutions should be empirically evaluated in terms of usability, efficiency, and impact on decision-making processes, to ensure their practical value for end-users. These BI solutions can also be supported or enriched with natural language processing or AI techniques, allowing users, for example, to define BI queries through natural language tuned by knowledge from the underlying ontologies, namely the LDWOWL.

LDWOWL was designed to formally and semantically store information concerning the DW's conceptual and logical models as a means to relate this knowledge to other domains (such as strategy). Notwithstanding, this "light" ontology, as the name suggests, does not cover the entire scope of the DW/BI domain but is limited to some aspects of requirements analysis and dimensional modeling, particularly for star schemas. For example, concepts such as aggregated and derived fact tables,[13] while taken into account, were not tested, and some advanced concepts (e.g., Bridges[14]) and variable depth hierarchies (i.e., ragged hierarchies) were not taken into account. Moreover, although the queries follow the standard BI query structure, which typically emphasizes conjunctive filtering and aggregation along dimensional attributes, the ontology does not cover the full complexity of real-world scenarios, especially ad hoc queries. For example, it lacks support for nested queries and other logical connectives such as disjunctions between multiple filter clauses. Although derived fact tables are commonly used to preserve the simplicity of model exploration when computing more complex indicators (i.e., model exploration follows the BI query pattern), extending the ontology to support more expressive queries would enhance its applicability to real-world analytical scenarios. In addition, the current method for transforming LDWOWL's queries into SQL, in the LDWOWL API, is limited to single-fact queries and to following the typical BI query pattern, further restricting the execution of more complex analytical scenarios. Hence, there are many opportunities for further exploration in future research.

The current development of the LDWOWL was idealized as a proof-of-concept. A formal ontology development methodology was not followed during the scope of this work, and the ontology was not formally validated (with tools such as OOPS! - Ontology Pitfall Scanner! [44]) or evaluated (by using competency questions). The full scope, impact, and potential of this ontological artifact, along with its robustness and general applicability, should be investigated in future research, independently of the presented framework, and supported by the application of formal ontology development methodologies. Most established methodologies, including METHONTOLOGY [45], On-To-Knowledge [40], NeOn [46], and the more recent Linked Open Terms (LOT) methodology [47], provide structured processes to define ontology requirements and offer guidance for ontology development, validation, evaluation, and maintenance. Recent studies show that using formal methodologies leads to more

[13]Derived fact tables include Accumulating Snapshots, Periodic Snapshot, and Merged fact tables [43].

[14]Bridges are used to model many-to-many relationships in a star schema, typically for multi-valued dimensions or multi-valued attributes [43].

robust and interoperable ontologies, especially when built on established standards. For example, Nostro et al. [48], [49] demonstrate how following a structured development process and aligning with a common foundational ontology can improve usability and integration. Adopting a similar approach could strengthen the design and applicability of LDWOWL. Further, the use of SW techniques, such as SWRL, SHACL, and SPARQL, for knowledge validation and inference should continue to be explored.

Although the LNEC case study is a compelling demonstration of the framework's applicability, its generalizability should be investigated through its application in other public and private organizations, and across strategy levels. As mentioned in Section VI, the applicability of the framework depends on two prerequisites: the existence of a DW and the formal definition of the strategy through a BSC. These conditions were met in the context of LNEC. However, in other organizations, preliminary work may be necessary before the framework can actually be applied, including formalizing the strategy or the development of a DW/BI system. In addition, the automation of the ontology instantiation process (for the BSO, LDWOWL and their link) should also be further explored to facilitate its application in other scenarios.

Finally, the evolution of real-world domains represented by ontologies, such as changes in organizational strategies, can pose significant challenges. While modifications to the DW schema would result in a new instantiation of the LDWOWL, as it serves as the semantic representation of the current in production schema, changes in organizational strategies, which are both incentivized and common, lead to the creation of new BSCs. The capability of exploring a BI environment with multiple BSC versions or instances is a current challenge that requires future research to provide a historical perspective of previous versions of strategic objectives and KPI.

VIII. CONCLUSION

This paper introduced an integration framework aimed at supporting the integration, alignment, and traceability between strategic models and the organizational IS necessary for providing data to the BSC's performance indicators, effectively bridging the gap between strategy definition and data. The Balanced Scorecard Ontology, introduced in previous works [33], [38], is used to formalize the strategy from a public organization (see Section II-B1), and the Light Data Warehouse Ontology is designed and developed to represent DW's conceptual and logical models.

The use of SW techniques streamlines data sharing across systems and organizations, facilitating efficient data collection, analysis, and reporting of performance indicators. The Integration Framework provides a semantic layer to integrate and align strategic models with organizational DW/BI. This alignment allows for the automatic retrieval of performance indicator values, increasing monitoring frequency with reduced human intervention and minimizing the probability of errors. This interoperability also supports compliance and governance initiatives by improving external communication and alignment with regulatory requirements, enabling automatic evaluation and reporting of compliance indicators. Furthermore, this integration enables empirical data-driven validation of the strategy formulation and ensures the alignment between data and performance indicators.

Moreover, the integration enriches conventional performance analysis conducted through DW/BI systems by incorporating strategic context, such as targets and objectives. This enhancement provides managers with deeper insights into how decisions align with broader organizational goals, improving the decision-making process's efficiency, quality, and timeliness. Overall, the integration of SW techniques in DW/BI systems empowers managers with user-friendly information and tools, enabling informed, data-driven strategic decisions aligned with the organizational strategy.

This research contributes to a holistic view of an organization, which can lead to a more realistic and cost-effective implementation of the strategy. The need to ensure that strategies remain comprehensive, transparent, and flexible is still at the forefront of BSC research, which points to integrated reporting mechanisms as one of the growing trends [50]. In fact, the effective execution of the Execution Premium Process (see Figure 4) relies heavily on access to accurate, timely, and relevant data from various sources, requiring a reliable monitoring of KPI and strategic objectives. Furthermore, achieving alignment across different departments and organizational levels is critical for the successful execution of the strategy. The critical importance of aligning organizational processes, resources, and actions with strategic objectives, as emphasized by Kaplan and Norton [31] enables organizations to effectively execute their strategies, fostering accountability and promoting continuous improvement.

APPENDIX A
ACRONYM TABLE

BI	Business Intelligence
BSC	Balanced Scorecard
BSO	Balanced Scorecard Ontology
DL	Data Lake
DLH	Data Lakehouse
DSS	Decision Support Systems
DW	Data Warehouse
KPI	Key Performance Indicators
LDWOWL	Light Data Warehouse Ontology
SW	Semantic Web

APPENDIX B
SUPPLEMENTARY MATERIALS

All ontologies used, namely BSO, LDWOWL and their link, are stored and available in the GitHub repository: https://github.com/Alorvaoa/BSO-LDWOWL

REFERENCES

[1] B. Burton, L. Geishecker, K. Schelegel, B. Hostmann, T. Austin, G. Herschel, A. Soejarto, and N. Rayner, "Business intelligence focus shifts from tactical to strategic," Gartner, Stamford, CT, USA, Tech. Rep. G00139352, 2006.
[2] D. J. Power, *Decision Support Basics*. New York City, NY, USA: Bus. Expert Press, 2009.
[3] R. Sharda, D. Delen, E. Turban, J. Aronson, and T. Liang, *Business Intelligence and Analytics*, 10th ed., London, U.K.: Pearson Edition Limited, 2015.
[4] Q. Yang, M. Ge, and M. Helfert, "Analysis of data warehouse architectures: Modeling and classification," in *Proc. 21st Int. Conf. Enterprise Inf. Syst.*, vol. 2. SciTePress, 2019, pp. 604–611, doi: 10.5220/0007728006040611.
[5] A. A. Harby and F. Zulkernine, "From data warehouse to lakehouse: A comparative review," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Dec. 2022, pp. 389–395.
[6] M. Breslin, "Data warehousing battle of the giants," *Bus. Intell. J.*, vol. 7, pp. 6–20, Apr. 2004.
[7] L. Yessad and A. Labiod, "Comparative study of data warehouses modeling approaches: Inmon, kimball and data vault," in *Proc. Int. Conf. Syst. Rel. Sci. (ICSRS)*, Nov. 2016, pp. 95–99.
[8] W. H. Inmon, *Building the Data Warehouse*. Hoboken, NJ, USA: Wiley, 2005.
[9] R. Kimball and M. Ross, *The Data Warehouse Toolkit: The Definitive Guide to Dimensional Modeling*. Hoboken, NJ, USA: Wiley, 2013.
[10] P. Sawadogo and J. Darmont, "On data lake architectures and metadata management," *J. Intell. Inf. Syst.*, vol. 56, no. 1, pp. 97–120, Feb. 2021.
[11] M. Y. Santos and C. Costa, *Big Data: Concepts, Warehousing, and Analytics*. Boca Raton, FL, USA: CRC Press, 2022.
[12] B. Inmon, M. Levins, and R. Srivastava, *Building the Data Lakehouse*. Sedona, AZ, USA: Technics Publications, 2021.
[13] B. Inmon, *Data Lake Architecture: Designing the Data Lake and Avoiding the Garbage Dump*. Sedona, AZ, USA: Technics publications, 2016.
[14] G. Phillips-Wren, M. Daly, and F. Burstein, "Reconciling business intelligence, analytics and decision support systems: More data, deeper insight," *Decis. Support Syst.*, vol. 146, Jul. 2021, Art. no. 113560.
[15] P. P. Khine and Z. S. Wang, "Data lake: A new ideology in big data era," in *Proc. ITM web conferences*, vol. 17, 2018, p. 03025.
[16] F. Ravat and Y. Zhao, "Data lakes: Trends and perspectives," in *Database and Expert Systems Applications*. Cham, Switzerland: Springer, 2019, pp. 304–313.
[17] M. Zaharia, A. Ghodsi, R. Xin, and M. Armbrust, "Lakehouse: A new generation of open platforms that unify data warehousing and advanced analytics," in *Proc. CIDR*, vol. 8, 2021, pp. 1–28.
[18] B. Shiyal, "Modern data warehouses and data lakehouses," in *Beginning Azure Synapse Analytics: Transition from Data Warehouse to Data Lakehous*. Cham, Switzerland: Springer, 2021, pp. 21–48.
[19] S. T. March and A. R. Hevner, "Integrated decision support systems: A data warehousing perspective," *Decis. Support Syst.*, vol. 43, no. 3, pp. 1031–1043, Apr. 2007.
[20] J. K. Bryson and B. George, "Strategic management in public administration," in *Oxford Research Encyclopedia of Politics*. Oxford, U.K.: Oxford Univ. Press, 2020. [Online]. Available: https://doi.org/10.1093/acrefore/9780190228637.013.1396
[21] N. Ain, G. Vaia, W. H. DeLone, and M. Waheed, "Two decades of research on business intelligence system adoption, utilization and success—A systematic literature review," *Decis. Support Syst.*, vol. 125, Oct. 2019, Art. no. 113113.
[22] B. George, R. M. Walker, and J. Monster, "Does strategic planning improve organizational performance? A meta-analysis," *Public Admin. Rev.*, vol. 79, no. 6, pp. 810–819, Nov. 2019.
[23] J. M. Bryson, *Strategic Planning for Public and Nonprofit Organizations: A Guide to Strengthening and Sustaining Organizational Achievement*. Hoboken, NJ, USA: Wiley, 2018.
[24] M. Král, "20-year history of performance measurement in the local public sector: A systematic review," *Int. J. Public Admin.*, vol. 45, no. 9, pp. 726–740, Jul. 2022.
[25] Y. Yurtay, N. Yurtay, H. Demirci, E. A. Zaimoglu, and A. Göksu, "Improvement and implementation of sustainable key performance indicators in supply chain management: The case of a furniture firm," *IEEE Access*, vol. 11, pp. 41913–41927, 2023.
[26] P. Hitzler, "A review of the semantic Web field," *Commun. ACM*, vol. 64, no. 2, pp. 76–83, Jan. 2021.
[27] P. Ristoski and H. Paulheim, "Semantic Web in data mining and knowledge discovery: A comprehensive survey," *J. Web Semantics*, vol. 36, pp. 1–22, Jan. 2016.
[28] A. L. Antunes, E. Cardoso, and J. Barateiro, "Incorporation of ontologies in data warehouse/business intelligence systems—A systematic literature review," *Int. J. Inf. Manage. Data Insights*, vol. 2, no. 2, Nov. 2022, Art. no. 100131.
[29] R. Kimball, M. Ross, W. Thornthwaite, J. Mundy, and B. Becker, *The Data Warehouse Lifecycle Toolkit*. Hoboken, NJ, USA: Wiley, 2008.
[30] A. Castro, V. A. Villagra, P. Garcia, D. Rivera, and D. Toledo, "An ontological-based model to data governance for big data," *IEEE Access*, vol. 9, pp. 109943–109959, 2021.
[31] R. S. Kaplan and D. P. Norton, *The Execution Premium: Linking Strategy to Operations for Competitive Advantage*. Cambridge, MA, USA: Harvard Univ. Press, 2008.
[32] R. M. Grant, *Contemporary Strategy Analysis*. Hoboken, NJ, USA: Wiley, 2021.
[33] A. L. Antunes, E. Cardoso, and J. Barateiro, "The balanced scorecard ontology: A semantic approach to enhance strategy management," *IEEE Eng. Manag. Rev.*, early access, Aug. 26, 2024, doi: 10.1109/EMR.2024.3439880.
[34] R. S. Kaplan and D. P. Norton, *The Balanced Scorecard: Measures That Drive Performance*, vol. 70. Cambridge, MA, USA: Harvard Univ. Press, 1992.
[35] A. Tawse and P. Tabesh, "Thirty years with the balanced scorecard: What we have learned," *Bus. Horizons*, vol. 66, no. 1, pp. 123–132, Jan. 2023.
[36] F. Manes-Rossi, G. Nicolò, and D. Argento, "Non-financial reporting formats in public sector organizations: A structured literature review," *J. Public Budgeting, Accounting Financial Manage.*, vol. 32, no. 4, pp. 639–669, Oct. 2020.
[37] J. Kumar, N. Prince, and H. K. Baker, "Balanced scorecard: A systematic literature review and future research issues," *FIIB Bus. Rev.*, vol. 11, no. 2, pp. 147–161, Jun. 2022.
[38] A. Lorvão Antunes, J. Barateiro, and E. Cardoso, "Strategic analysis in the public sector using semantic Web technologies," *Digit. Government, Res. Pract.*, vol. 5, no. 3, pp. 1–20, Sep. 2024, doi: 10.1145/3656587.
[39] A. L. F. Antunes, "Application of semantic Web techniques in data warehouse and business intelligence systems," Ph.D. dissertation, Dept. Inf. Sci. Technol., Instituto Universitario de Lisboa, Lisbon, Portugal, 2024.
[40] S. Staab, R. Studer, H.-P. Schnurr, and Y. Sure, "Knowledge processes and ontologies," *IEEE Intell. Syst.*, vol. 16, no. 1, pp. 26–34, Jan. 2001.
[41] J. Barateiro, P. Couto, A. Antunes, A. Sebastião, and M. A. Santos, "Enquadramento estratégico do lnec-proposta de mapa estratégico," National Laboratory for Civil Engineering (LNEC), Lisbon, Portugal, Tech. Rep. RELATÓRIO 446/2021–CD, Sep. 2021.
[42] L. Corr and J. Stagnitto, *Agile Data Warehouse Design: Collaborative Dimensional Modeling, From Whiteboard to Star Schema*. U.K.: DecisionOne Press, 2011.
[43] C. Adamson, *Star Schema the Complete Reference*. New York, NY, USA: McGraw-Hill, 2010.
[44] M. Poveda-Villalón, A. Gómez-Pérez, and M. C. Suárez-Figueroa, "OOPS! (OntOlogy pitfall scanner!): An on-line tool for ontology evaluation," *Int. J. Semantic Web Inf. Syst.*, vol. 10, no. 2, pp. 7–34, Apr. 2014.
[45] M. Fernández-López, A. Gómez-Pérez, and N. J. Juzgado, "Methontology: From ontological art towards ontological engineering," in *Proc. AAAI Conf. Artif. Intell.*, 1997. [Online]. Available: https://api.semanticscholar.org/CorpusID:10550105
[46] M. C. Suárez-Figueroa, A. Gómez-Pérez, and M. Fernández-López, "The NeOn methodology for ontology engineering," in *Ontology Engineering in a Networked World*. Cham, Switzerland: Springer, 2012, pp. 9–34.
[47] M. Poveda-Villalón, A. Fernández-Izquierdo, M. Fernández-López, and R. García-Castro, "LOT: An industrial oriented ontology engineering framework," *Eng. Appl. Artif. Intell.*, vol. 111, May 2022, Art. no. 104755.
[48] P. Del Nostro, G. Goldbeck, A. Pozzi, and D. Toti, "Modeling experts, knowledge providers and expertise in materials modeling: MAEO as an application ontology of EMMO's ecosystem," *Appl. Ontol.*, vol. 18, no. 2, pp. 99–118, Aug. 2023.

[49] P. Del Nostro, G. Goldbeck, F. Kienberger, M. Moertelmaier, A. Pozzi, N. Al-Zubaidi-R-Smith, and D. Toti, ''Battery testing ontology: An EMMO-based semantic framework for representing knowledge in battery testing and battery quality control,'' *Comput. Ind.*, vol. 164, Jan. 2025, Art. no. 104203.

[50] S. Kumar, W. M. Lim, R. Sureka, C. J. C. Jabbour, and U. Bamel, ''Balanced scorecard: Trends, developments, and future directions,'' *Rev. Managerial Sci.*, vol. 18, no. 8, pp. 2397–2439, Aug. 2024.

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