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Knowledge-Based Engineering in Strategic Logistics Planning

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Abstract

Strategic logistics planning is used by management to define action plans that will enable organizations to always make decisions that are in the organization's best interests. They are based on a knowledge repository of business experiences, which is usually represented by a centralized, organized, and searchable digital system where organizations store and manage critical institutional knowledge. Thus, an institutional knowledge base provides sustainability, making the experiences readily available while keeping them well organized. In this research, the experiences of logistics experts from selected scholarly designs for six-sigma business improvement projects have been collected, classified, and organized to form a logistics knowledge management system. Although originally meant to facilitate current and future decisions in strategic logistics planning of the cooperating companies, it is also used in logistics education to introduce knowledge-based engineering principles to enterprise strategic planning, based on continuous improvement of quality-related product or process performance indicators. The main goal of this article is to highlight the benefits of knowledge-based engineering over the established ontological logistics knowledge base in smart production, based on the predisposition that ontological institutional knowledge base management is more efficient, adaptable, and sustainable.

Keywords: logistics; knowledge-based engineering; ontology; sustainable

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1. Introduction

In the dynamic and modern business environment, the greening of supply chains has emerged as a key priority for organizations striving to foster sustainability and operational efficiency. This acceleration towards sustainability is supported by strategic logistics planning, integrating decision-making frameworks with organizational objectives and environmental stewardship [1,2]. Sustainability transformations are crucial, as global supply chains face severe pressures from regulatory demands, consumer expectations for environmental practices, and the need to adapt to unpredictable disruptions [3]. Thus, organizations are required to rethink existing logistics approaches to align their sustainability and competitiveness agendas in a globalized economy. This dual focus on greening, on the one hand, increases efficiency, while on the other hand, underscores the urgency of developing innovative strategies that can address both economic and ecological imperatives in an increasingly interconnected global economy.

Strategic planning seeks to acquire a company's success and competitive positioning, necessitating robust frameworks to guide logistics operations [4]. These operations are often represented in information systems via logistics models, outlining the interplay of activities, organizations, transportation methods, goods, and services involved in logistics processes. However, a significant drawback of many current models is their lack of formal semantics, impeding automated data integration across organizational boundaries [5]. This lack of standardization often results in fragmented data ecosystems, intensifying real-time decision-making and coordination among supply chain partners [6]. Strategic logistics planning addresses these challenges by establishing action plans that empower management to make informed decisions aligned with organizational interests. Such an organized repository of business experiences from the institutional knowledge base enhances decision-making by leveraging past insights [7]. Thus, the institutional knowledge base of experiences, which have been accumulated over years of operational practice, serves as a critical asset for identifying best practices and avoiding past pitfalls [8]. By tapping into this knowledge base, companies can embed sustainability into their logistics strategies, ensuring environmental considerations are prioritized alongside operational efficiency. Such an approach also mitigates risks associated with supply chain disruptions, a growing concern in volatile markets [9]. Addressing these challenges requires innovative approaches to business model design that prioritize flexibility and scalability to meet evolving industry demands [10]. Enhancing logistics models using an institutional knowledge base could unlock significant competitive advantages by streamlining processes, reducing waste, and improving responsiveness across global networks [11]. By leveraging this knowledge base, companies can ensure that sustainability is seamlessly integrated into their logistics strategies. Yet, the limitations of current models, such as their lack of formal semantics, highlight the need for advanced ontological approaches that standardize and enrich logistics knowledge bases, enabling seamless interoperability [12].

An ontology seeks to formalize a language and definitions for domain-related communications, thus enhancing the sharing of meaning across relevant stakeholders. According to [13], a strategic ontology for enterprises is no exception, as it provides a structured lens through which complex logistics interactions can be understood and optimized. Identifying patterns in business-level typologies advances the ontology by informing strategy direction within competitive environments. These ontologies not only improve data sharing, but also foster sustainable supply chain practices by aligning resource allocation considering environmental goals [14]. Usually, when processing knowledge bases, the knowledge-based engineering (KBE) approach is used, which integrates knowledge bases into engineering processes to automate, optimize, and enhance design, planning, or operational tasks. KBE formalizes knowledge into reusable models, reducing time and errors in complex applications, which is valuable when decisions need to be fast, repeatable, and informed by deep expertise [15]. Furthermore, integrating these knowledge bases with emerging technologies, such as artificial intelligence, can optimize decision-making and enhance resilience in increasingly complex global networks [16]. This digital transformation is crucial for adapting to disruptions, as evidenced by the growing adoption of artificial intelligence-driven predictive analytics in logistics [17].

The convergence of ontology and technology also enables proactive risk management, allowing firms to anticipate and respond to challenges before they emerge or even escalate [18]. Such advancements, using ontology foster a more cohesive and adaptive logistics ecosystem, capable of meeting both operational and sustainability demands while paving the way for long-term organizational success. Furthermore, these improvements can position companies to evolve in market dynamics, contribute to a more sustainable global supply chain landscape, and set a foundation for future research into scalable, knowledge-driven logistics solutions.

To demonstrate the usefulness of knowledge bases and knowledge-based engineering, we have carried out research, categorizing and structuring logistics experts' experiences into an ontological logistics knowledge base. This ontological approach integrates insights derived from design for six sigma business improvement projects, forming a coherent framework that enhances decision-making for both present and future strategic logistics planning, which can be further integrated into green and sustainable supply chain management-related courses.

The paper introduces various examples regarding the usage of the established ontological logistics knowledge base for knowledge management in companies. Experts, analysts, and managers share insights on how this organized framework improves their ability to address complex logistics challenges, including sustainability agendas, such as the following:

- Expert Insights: Experts can quickly retrieve case studies or best practices related to sustainable logistics initiatives, streamlining their research and application efforts.
- Analytical Perspectives: Analysts can utilize the knowledge base to run simulations and predict outcomes based on historical data, allowing for data-driven strategic planning.
- Managerial Applications: Managers can easily access strategic recommendations that align with sustainability goals, ensuring that their decisions are informed by collective experiences and proven methodologies.

This paper is organized into four sections. Research Placement discloses relevant research topics and gaps, using Leximancer software. The Methods and Tools section introduces the domain-specific and cross-domain methodologies used in the conceptualization of the proposed approach. In the Results section, an illustrative use case is given, followed by a Discussion, providing an in-depth interpretation of the findings. The Conclusions section summarizes the key insights and takeaways from the study.

2. Research Placement

For an in-depth overview of current research on the topic of sustainable supply chain management and a better understanding of the importance and identification of potential gaps, we conducted an additional analysis of existing published research. In the first step, we conducted several search queries in the two most expansive and scientifically supported databases, Web of Science (WoS) by Clarivate and Scopus by Elsevier, with the initial searches conducted on the 26th and 27th of November 2024, respectively. In both databases, three search queries were carried out, with additional limitations focusing only on publications published from 2019 to the date of search, written in English, and being an article, review article, or book. Following the initial settings, additional screening further reduced the number of identified papers, with the first screening focusing on the paper's title and abstract, and the second on the entirety of the paper's content and its contextual semblance on the searched keywords. The results of each search and the two screenings can be observed in Table 1.

Following the merging of the identified papers from each search query and database, we ended up with a collection of 242 papers. The next step was using Leximancer software to conduct a contextual analysis. Leximancer is a software designed to analyze large collections of textual documents and graphically visualize the results based on users' inputs. The software builds high-level concepts and themes through rigorous statistical techniques and applies both neural and contextual semantics between identified words. By creating a concept map, the software visualizes intricate connections and inter-dependencies between concepts, which the user can interpret [19]. Using Leximancer, we constructed a concept map with five distinct themes, represented as circular shapes with different color schemes (see Figure 1). In this representation, brighter colors (e.g., red) represent themes of higher importance in the analysis, whereas colder ones (e.g., dark blue) represent themes of lower importance [20]. The most prominent theme identified was knowledge base, followed by ontology, entity, rules, and supply chain.

Table 1. Cross-referencing research topics.

Database	Search Query	No. of Hits	1st Screening	2nd Screening
Scopus	"ontology" AND "six sigma" AND "knowledge base"	59	49	35
Scopus	"ontology" AND "six sigma" AND "knowledge-based engineering"	11	9	7
Scopus	"ontology" AND "Knowledge base" AND "engineering"	8443	4738	171
WoS	"ontology" AND "six sigma" AND "knowledge base"	3	1	1
WoS	"ontology" AND "six sigma" AND "knowledge-based engineering"	1	1	1
WoS	"ontology" AND "Knowledge base" AND "engineering"	1457	649	74

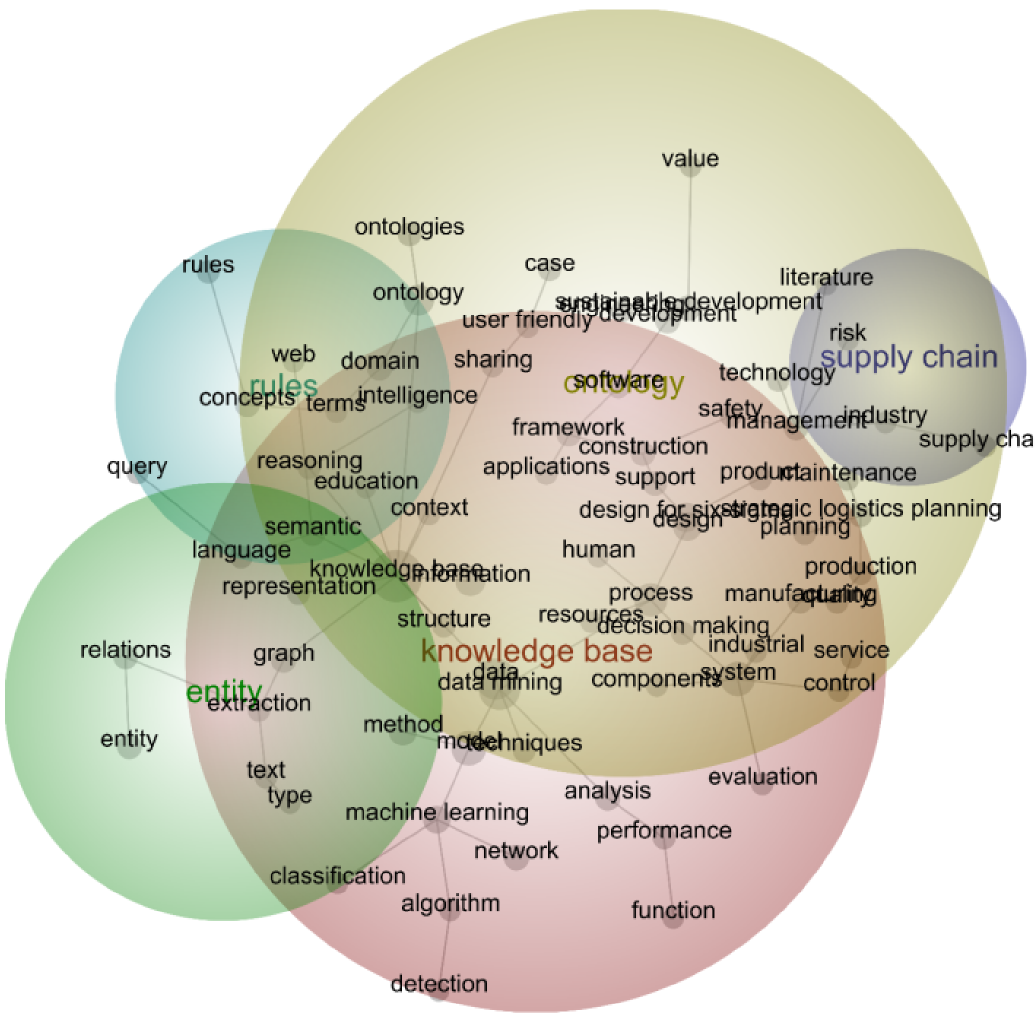

Figure 1. Concept mapping.

As observed in the concept map, all themes overlap significantly, indicating a strong interconnection in contextual backgrounds. This overlap reflects that the analyzed publications address several intersecting research areas. Some concepts were included under multiple themes to interpret the results better and capture the thematic interrelations. A deeper insight into the theme knowledge base identified 31 concepts within the theme, which could be grouped into three distinct concept clusters. The first and most prominent concept cluster consists of "data mining", "data", "information", "system", "process", "machine learning", "algorithm", and "decision making", indicating that the research is focusing on the development of methods that enable collection and processing of large data volumes in datasets and databases through the usage of machine learning, data mining, and semantic approaches in structured knowledge systems [21] and finally evaluate the quality of the data [22]. The second concept cluster centered around "design for six-sigma", "design", "product", "engineering", "manufacturing", "process", "planning", and "human", suggesting research into applying knowledge bases to improve industrial processes [23], involving optimizing and enhancing system processes by implementing design for six-sigma principles supported by structured knowledge systems [24]. The third cluster included the concepts "knowledge base", "semantic", "graph", "representation", "intelligence", "reasoning", and "structure", aligning with the development of knowledge graphs, semantic webs, and AI-powered decision systems, designed to enable predictive analytics, automation, and self-learning capabilities, which can offer solutions for structured data representation and intelligent decision-making [25].

The second most prominent theme was ontology, for which two concept clusters were identified, with the first one encompassing concepts "ontology", "ontologies", "domain", "intelligence", and "domain". The cluster focuses on research into developing domain-specific ontologies [26] for predetermined industry sectors and research fields. Such ontologies, in turn, provide standardized domain knowledge, forming the foundation for AI systems [27], reasoning frameworks, and interoperable structures, which can enable improved communications across systems [28] and among stakeholders within specific domains [29]. The second cluster consisted of "software", "development", "sustainable development", "framework", "construction", "applications", "safety", and "support", indicating research into the development of both sustainable and adaptable ontology frameworks [30]. Sustainable frameworks, in particular, prioritize and help achieve resource efficiency, safety, and usability, while supporting practical software applications, enhancing safety and risk management in existing systems [31], ensuring their reliability, and promoting collaboration and knowledge sharing through advanced tools or frameworks [32].

The third most prominent theme was entity, where the concept cluster included the concepts "entity", "relations", "extraction", "language", "text", "classification", "graph", and "type". The concepts reflect research into developing methods for extracting entities and defining relationship between them, with an emphasis on using natural language processing technologies (NLP). The NLP technologies can parse, analyze, and interpret human language, enabling the extraction of meaningful structures from unstructured text [33] and help with building knowledge bases [34]. Another research focus which could be identified was the classification and structuring of entities, involving assigning categories and types to better represent entities in more structured formats such as graphs [35]. The indices towards such development can be observed in the concept and theme overlaps, which indicates the development of knowledge graph modeling, which improves the structuring of extracted entities into relational models for use in either decision-making or analytical activities [36].

The fourth theme was rules, where the concept cluster consisted of concepts "rules", "concepts", "web", "query", "terms", "intelligence", "education", and "reasoning". The concepts suggest research oriented towards rule-based knowledge representation and reasoning. Incorporating formalized rules and concepts to infer new knowledge into systems can establish supporting decision-making processes or automation of reasoning tasks [37]. Another identified focus is the development of intuitive and intelligent query mechanisms for accessing structured knowledge in either web-based or semantic environments. Such query mechanisms aim to improve both user interaction with complex knowledge systems and enable efficient retrieval of relevant information [38].

The least prominent theme was supply chain, which included concepts “supply chain”, “industry”, “management”, “risk”, “technology”, and “management”. The supply chain theme overlaps with the ontology theme, suggesting a research focus on integrating semantics into the existing supply chain systems. Such an integration aims to enhance real-time tracking and decision-making in supply chain networks [39], through the utilization of tools for evaluation and ontology-driven metrics. Additional indices include research into the ontology-based platform development, which is needed for scenario modeling and risk mitigation, which, in turn, both improve the resilience and efficiency within supply chains [40].

The Leximancer analysis highlights a significant research focus on the selected keywords and their associated areas. The concept map generated from this analysis illustrates the strong interconnections among themes, concepts, and keywords, suggesting a parallel research relationship characterized by knowledge sharing and collaborative development. The findings reveal that ontology, knowledge bases, engineering, and six sigma are interrelated and mutually dependent in ongoing research efforts, with advancements in one domain influencing progress in the others.

3. Materials and Methods

The herein applied research methods can be categorized as qualitative research based on case studies. By their nature, descriptive and analytical research methods are combined to synthesize the various concepts and formalize them to form an ontology. By its purpose, this research falls both into fundamental and applied research methodologies, since on the one hand, a conceptualization is completed, whilst on the other, concrete use cases are investigated. However, since this research is conducted on preexisting concepts and data, it can be qualified as secondary research. To fulfill its purpose as a conclusive study, the main research question to be answered here is to prove the predisposition of the original fundamental research, stating that “ontological institutional knowledge base management is more efficient, adaptable, and sustainable”.

3.1. Methods

Strategic logistics planning entails formulating approaches and structured activities that guide organizations toward fulfilling their objectives. This strategic planning process enables management to establish coherent action plans, ensuring that decision-making consistently aligns with organizational priorities and interests. Such planning frameworks are fundamentally rooted in the concept of institutional knowledge.

Institutional knowledge is typically governed via business intelligence (BI) methods, encompassing a range of strategies and technologies for analyzing and systematically managing business data and information. In conjunction with business analytics (BA) and knowledge-based engineering (KBE) approaches [41], these methods support the development of informed decisions aimed at sustaining or enhancing organizational performance and competitive positioning in the market.

Although institutional knowledge often originates from the expertise of individuals, it is advisable to preserve this knowledge in a structured and enduring format. Standard practice involves capturing such knowledge through business improvement projects. However, this approach can become inefficient over time for two key reasons:

1. It tends to grow considerably over time and become scattered;

2. With the growth of the archive in size and complexity, the time it takes to find information on a particular project may grow exponentially.

From the BI perspective, these challenges highlight the need for more advanced and structured approaches to institutional knowledge management. As data storage technologies have developed from traditional databases to data warehouses and subsequently to cloud-based architectures, the logical progression also includes migrating and transforming the organizational knowledge bases. In the course of this, in [42], a semantic web approach to managing business experiences and supporting online analytical processing (OLAP) technologies has been proposed.

The need to capture, manage, and utilize design knowledge and automate decision-making processes unique to a manufacturer's product development has led to the introduction of KBE into smart production. KBE comprises a number of intertwined methods that systematically address the common institutional knowledge base to achieve planned results:

- Computer-aided project management (PS);
- Computer-aided design (CAD), production (CAM), and robotics (CIM);
- Computer simulation modeling and analysis (SMA);
- Computer-aided detailed production planning (MPS/MRP).

Within this research, they have been systematically integrated into the ontological knowledge base (KB) of the logistics knowledge management system (LKMS). Acting as a primary source of information in business improvement projects, the goal was to build an expert system that would support the different levels of management in their decisions.

Aligned with the principles of KBE and design for six sigma (DFSS) [43], the knowledge management lifecycle within the LKMS is structured around the iterative application of Deming's OPDSA (Observe–Plan–Do–Study–Act) cycle [44]. This framework enables systematic learning and continuous improvement through the following stages:

1. Detection of deviations from the intended state within manufacturing processes, typically arising from inadequately defined products or processes.
2. Documentation of the observed experience, emphasizing its distinctive characteristics.
3. Executing root cause analysis based on the identified symptoms to formulate a targeted corrective or preventive strategy.
4. Integrating analytical insights into the institutional knowledge base, formalizing the experience for future reference and reuse.

As deduced from this experience lifecycle, the integrated application of the aforementioned methods yields actionable outcomes, facilitating systematic and controlled organizational change in alignment with DFSS business improvement strategies. Their consequences are again analyzed to determine possible further improvements, hereby closing the PDCA (Plan–Do–Check–Act) circle of continuous improvement. Since these findings enrich the organization's institutional knowledge, they are again included in its common knowledge base.

Hence, according to SCOR [45], KBE represents integrating continuous improvement principles into strategic enterprise planning, guided by quality- oriented performance indicators related to products or processes.

3.2. Tools

Companies generate large amounts of data on every front. Whether it is internal knowledge, materials specifications, manuals, or business process data, the amount of information is huge. The challenge that comes with it is to collect, store, and make it easily accessible to a wider audience. That is where knowledge management tools are used. These tools help businesses collect and manage information among employees and customers. Storing and organizing knowledge helps the organization improve processes, workflows, and, in the long run, make better business decisions. Sharing knowledge with customers, on the other hand, provides them with customer self-service. There are many knowledge management tools to choose from—from knowledge bases and wikis to learning and knowledge management software tools. They are described and compared in detail in [46]. For managing tactical and operational business process-related data, Enterprise Resource Planning (ERP) systems are being used. In combination with Business Intelligence (BI) and modern Supply Chain Management (SCM) tools, they provide a framework for smart production; however, strategic decision-making supporting KBE's knowledge management lifecycle is essential. It provides for the reuse of past experiences gained by business improvement projects for business optimization.

The methods in the previous section address strategic logistics planning from different perspectives and levels of decision-making, supporting the knowledge management lifecycle of KBE. By the logistics knowledge management system (LKMS), an expert system has been defined, which utilizes experience-based strategic logistics planning for business improvement on the principles of KBE [42].

The LKMS's KB represents institutional knowledge, being managed in the form of an ontology [47] of business improvement experiences [48]. As indicated in Figure 2, it is composed of three distinct types of artifacts: entities, attributes, and relations. Properties, represented by attributes, have a specific type and value. Relations, on the other hand, introduce links to other entities, representing their associations. On the other hand, English controlled natural language (ECNL), based on predicate logic with facts and rules, can be used interchangeably [42]. Such a context-based KB organization eases the retrieval of information from the KB while keeping it compact and well-organized.

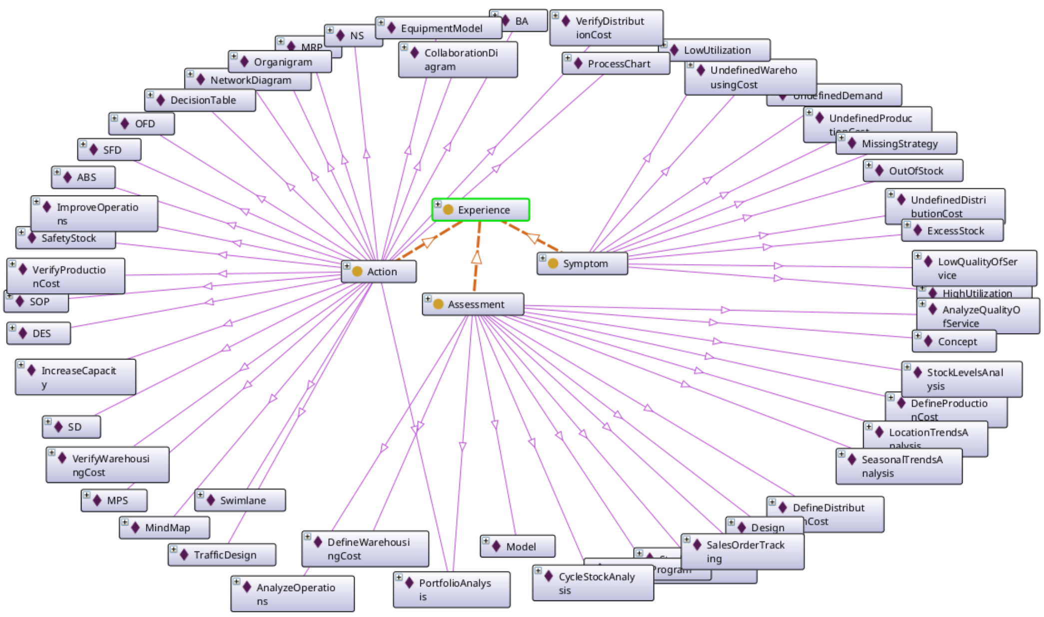

Figure 2. LKMS ontology graph.

Two ontology management tools, namely Stanford's Protege (https://protege.stanford.edu/ (accessed on 24 July 2025)) and Cognitum's Fluent Editor (www.cognitum.eu/semantics/FluentEditor/ (accessed on 24 July 2025)), have been used by domain experts and analysts to construct, access, maintain, and retrieve information from the LKMS. Apart from accessing the LKMS's KB directly via the aforementioned ontology management tools, they can be made accessible via a knowledge base server through a semantic web service, like Apache Jena's Fuseki (https://jena.apache.org/ (accessed on 24 July 2025)) server, or via online analytic processing (OLAP) [49] tools (e.g., using Cognitum's Python, R-language plug-ins).

4. Results

The proposed logistics knowledge management system (LKMS) represents an expert system for collecting, cataloging, and retrieving business process design experiences that are stored in its knowledge base.

While the system can store a wide range of information, its most crucial content consists of context-aware business improvement experiences. These entries serve as essential resources for addressing specific operational challenges related to production efficiency, contingency planning, and sustainability. They embody institutional knowledge analysts, experts, and managers, who are drawn upon during organizational decision-making processes via the enterprise LKMS.

Our LKMS builds on a catalog of experiences from multiple DFSS business improvement projects (see Appendix A) and is primarily meant for study purposes. The collected experiences are represented as entities that can be retrieved and combined in various ways. Each experience in LKMS KB is represented by the symptoms, assessment methods, and action plans (see Figure 2). Action plans can be layered across different levels of decision-making. Experiences can be grouped into DFSS projects where, according to DFSS, diverse experiences address the distinct phases of business improvement projects.

There are various ways to retrieve knowledge from the LKMS's logistic knowledge base. The most straightforward one is to use the associated knowledge management tools (e.g., Fluent Editor, Protege, etc.) with their knowledge aggregation, classification, and representation mechanisms. However, this may be impractical for non-expert users. The aforementioned programming/statistical language interfaces may be used for OLAP in advanced planning and scheduling (APS) systems. By issuing appropriate SPARQL queries to the LKMS semantic web server, the desired results can be obtained.

Use Case

In one of our typical student-assisted projects with the industry, our partner was seeking advice on the improvement of their production process. They were exploring different ways to improve their production capability. Although at first it seemed the company only needed a second production line to handle the increased workload, it turned out that the production capacity of the existing production line was poorly used. Hence, a multilevel business improvement project was necessary in order to investigate, plan, and implement the necessary changes. The DFSS business improvement project Dfss-1 comprises experiences gained with the partner company. It is composed of combinations of multiple methods within experiences, pertaining to individual DFSS phases, with Scex-1-1 representing the define phase and Scex-2-1 to Scex-5-1 representing the monitor, analyze, design, and verify phases, respectively (Table 2). These experiences have been included in the ontology-based knowledge base of LKMS to assist in further research and future business improvement projects.

Scex-1-1 defines the company's system model with its key components and processes on the strategic, tactical, and operational levels, thus making it manageable. Various design methods (e.g., mind-maps, organigrams, process-charts, decision-tables, swim-lane diagrams, object-flow diagrams, equipment, data, and service models) have been applied to formalize conceptual and logical models of the company. Based on these insights, students could grasp the physical production process characteristics and the environmental conditions in which the company operates. At the same time, they also identified its properties, being explored in the subsequent phases.

Table 2. Classification of Dfss-1 experiences.

Experience	Phase	Scope	Type	Focus
Scex-1-1	define	strategic, tactical, operational	strategy-formulation, operations-planning	capacity-planning
Scex-2-1	monitor	strategic, tactical, operational	strategy-formulation, operations-planning	performance-monitoring, capacity-planning
Scex-3-1	analyze	tactical, operational	operations-planning	performance-monitoring, capacity-planning
Scex-4-1	design	tactical, operational	operations-planning	capacity-planning
Scex-5-1	verify	operational	operations-planning	performance-monitoring

In Scex-2-1, a physical model of the company has been devised to allocate and measure the current state (AS-IS) of the company's relevant key performance indicators (KPIs) (e.g., stock levels, utilization of production capacities). Here, business analytics and simulation methods (cp. [50]) have been used to assess the company's KPIs and put them into the strategic context of the problem at hand.

By Scex-3-1, the KPIs have been analyzed on the tactical (e.g., business analytics) and operational levels (e.g., discrete event simulation) to identify the shortcomings. They have been assessed to predict possible improvements by materials and resource planning methods (capacity planning and production scheduling).

In Scex-4-1, the identified shortcomings have been addressed by appropriate methods and measures at the same levels, on which they occur, and the best-case scenario (TO-BE) has been defined. By appropriate equipment design, as well as simulation modeling and analysis methods, the foreseen solution has been designed to enable its verification and validation. Both are important since the former determines the correctness of the designed model and the second its coherence.

The proposed solution has been verified and validated in Scex-5-1 to check whether the identified deficiencies have been properly addressed (e.g., production cost, warehousing cost), and further deficiencies (e.g., bottlenecks) prevented.

Although, the long-term impact of the proposed solutions is difficult to predict, one can foresee the side effects of their implementation and prevent their negative consequences by introducing appropriate business contingency measures (e.g., forecasting, materials requirements planning, and master production scheduling).

Considering the volume and level of detail in the descriptions of the acquired experiences in our LKMS, the contribution to its knowledge base may vary from project to project. It depends on the size as well as the structural, behavioral, and interaction complexity of the company's model, as well as its specifics. Nevertheless, its integration must be concise to enable automated knowledge retrieval and decision-making (e.g., using the aforementioned OLAP tools' search and retrieve mechanisms) in future (similar) DFSS projects.

5. Discussion

While the presented use-case from the proposed LKMS mainly serves as proof of concept and an in-class presentation example, an enterprise knowledge base may be more elaborate and complex. Nevertheless, the presented LKMS experiences are a good way to structure a next-generation contextual institutional knowledge base. Expressed in the Fluent Editor's ECNL language, the complexity of ontological knowledge representation is reduced, making it human-readable whilst retaining the benefits of its formal notation. The predicate logic representation of knowledge also retains the capability of automated reasoning using OLAP and natural language processing tools. By this, future business improvement projects can be derived faster and more accurately by just applying previous experiences on similar symptoms and adapting them to the problem at hand.

The LKMS expert system has proven to support managers and students alike in managing the complexity of strategic logistics planning and business process improvement. Our experience from in-class presentations has shown that the volume of information here is overwhelming and may lead to confusion among the students even when using the systemic approach. However, by systematically assessing the individual levels of strategic logistics planning, defining conceptual, logical, and physical models of a company, and concluding with a comprehensive business improvement project, the big picture regains focus. This also eases the navigation through the established logistics knowledge base and enables new ways of knowledge discovery and generation.

In relation to former research on smart production logistics [51], the herein introduced support for strategic production planning by the presented logistics knowledge management system (LKMS) underpins the efforts for a consistent and coherent digital model of a modern enterprise. The main benefits of LKMS's ontological institutional knowledge base organization are as follows:

- Enhanced clarity and usability: The structured context-aware organization of knowledge facilitates easier access to relevant information, making it simpler for decision-makers to find insights that pertain to their specific challenges.
- Sustainability integration: By systematically incorporating sustainability principles into the knowledge base, organizations can make greener choices that align with their overall strategic goals.
- Improved decision-making: With predicate logic-based knowledge discovery and management techniques, complex decision-making processes become more manageable and user-friendly. This approach allows for nuanced analyses that consider multiple variables and scenarios.
- Facilitated knowledge management: The ontological structure supports ongoing knowledge maintenance and updates, ensuring that the knowledge base remains coherent over time.
- Generations of managers, employees, and students can benefit from former knowledge stored in our LKMS and build on it.

6. Conclusions

This paper discusses different forms of institutional knowledge representation and management, with a focus on the application of the DFSS methodology in strategic logistics planning. In particular, its aim is to highlight the benefits of knowledge-based engineering over the established ontological logistics knowledge base in smart production. In contrast to other institutional knowledge management tools, semantic web and OLAP technologies have proven to be more efficient, adaptable, and sustainable.

Considering the identified benefits of ontological knowledge base management, the main research question regarding our LKMS expert system's knowledge base has been confirmed—an ontological institutional knowledge base is more efficient, adaptable, and sustainable. It is smaller and easier to navigate. It grows by its use; however, it never becomes cluttered since every new experience fits into place according to the LKMS internal organization. In consequence, the ontology-based LKMS expert system's KB is more sustainable, since it grows and ages with the company without degradation in its efficiency.

KBE in strategic logistics planning represents a pivotal shift toward sustainable business practices. By harnessing the LKMS's ontological KB of DFSS experiences, organizations can enhance their operational efficiency while committing to environmental stewardship. The integration of semantic web technologies and predicate logic-based knowledge discovery techniques not only improves knowledge management but also empowers organizations to navigate complex logistics landscapes with greater ease and effectiveness. As businesses continue to embrace sustainability, the role of KBE-based strategic logistics planning will be crucial in driving forward-thinking decisions that benefit both the organizations and their environment.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. DFSS SCM Experiences Catalog

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*******************************************************************
Phase: Define, Measure, Analyze, Design, Verify
Scope: strategic, tactical or operational
Type: network design, strategy formulation, operations planning
Focus: capacity planning, performance monitoring, quality assurance
*******************************************************************

Phase1 (Define)
!------------ Strategic -------------!
1. Conceptual modeling
1.1 Mind charts
1.2 Organizational charts
1.3 Process diagrams
!------------ Tactical -------------!
2. Logical modeling
2.1 Decision
Tables~2.2 Swim-lane diagrams
2.3 Object-flow diagrams
2.4 Stock-and-flow diagrams
!------------ Operational -------------!
3. Physical modeling
3.1 CAD/CAM modeling (IT modeling, Telecommunications modeling,
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Functional equipment modeling)
3.2 Data modeling (Spreadsheet, Database, Data-warehouse, Ontology)
3.3 Simulation modeling (DES, SD, ABS, NS)

Phase2 (Monitor)
!------------ Strategic -------------!
1. Portfolio analysis (BA, pivot table, DB)
2. Seasonal-trends analysis (BA, pivot table, DB)
3. Location-trends analysis (BA, pivot table, DB)
!------------ Tactical -------------!
4. Cycle-stock monitoring (BA, DES)
5. Stock-and-flow monitoring (BA, SD)
6. Service-quality monitoring (BA, ABS)
!------------ Operational -------------!
7. Sales-order tracking (BA, pivot table, DB)

Phase3 (Analyze)
!------------ Tactical -------------!
1. Production performance monitoring (BA, capacity planning, DES)
1.1 Utilization monitoring
2. Distribution performance monitoring (BA, capacity planning, SD)
2.1 Stock levels balancing
3. Warehouse performance monitoring (BA, capacity planning, SD)
3.1 Stock cost validation
3.2 Stock monitoring (min, max, signal, safety, cycle)
!------------ Operational -------------!
4. Optimization
4.1 Production cycle/capacity optimization
4.2 Economic order quantity (EOQ) optimization
4.3 Inventory turnover optimization
4.4 Transport capacity optimization
4.5 Total production cost (TC) optimization

Phase4 (Design)
!------------ Strategic -------------!
1. Project planning (OR)
1.1 Strategic logistics planning (P1)
!------------ Tactical -------------!
2. Sales and operations planning (SOP) (BA, pivot table, DB)
2.1 Demand program (DP)
2.2 Master Production Scheduling (MPS)
2.3 Master Resource Planning (MRP)
!------------ Operational -------------!
3. Computer integrated manufacturing (CIM)

Phase5 (Verify)
!------------ Operational -------------!
1. Logistics revision (conformance with DFSS strategy)
1.1 Target and actual KPI comparison
1.2 Perceived and actual KPI comparison
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1.3 KPI inter-dependency analysis
1.4 Critical operations identification
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