# Business Ecosystem Analysis & Representation Framework (BEAR): A Semantic Approach to Mapping Organizational Relationships and Supply Chain Interdependencies in Wind Energy

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**Abstract**

Traditional analytical frameworks often struggle to capture the complexity of business ecosystems, leading to ecosystem blind spots and missed opportunities. Following a semantic approach, we introduce the Business Ecosystem Analysis & Representation (BEAR) framework to uncover these blind spots. This approach leverages domain, seed ontologies, and empirical data to construct insightful knowledge graphs and context-driven visualizations, enabling question-driven analysis. Furthermore, we applied BEAR to the wind energy ecosystem to demonstrate its value using data from 35 companies extracted from WindEnergy Hamburg 2024. Guided by co-developed questions with industry experts from a leading manufacturer, our analysis revealed the BEAR's ability to map organizational positioning, interdependencies, and previously hidden wind energy ecosystem supply chain dynamics. These preliminary results demonstrate BEAR's effectiveness in unlocking deeper ecosystem understanding beyond syntactic methods, offering a scalable, semantic toolset that promises to advance strategic planning and ecosystem knowledge representation in business ecosystem analysis.

**Keywords**

Business Ecosystem, Ontology, Knowledge Graph, Business Ecosystem Analysis, Supply Chain Analysis, Wind Energy Ecosystem, Business Ecosystem Visualization

## 1. Introduction

Ecosystem blind spots—unseen interdependencies among competitors, regulators, and stakeholders—can cost organizations billions in lost market value and missed opportunities [1, 2]. These blind spots create existential threats to organizations because we argue that traditional analytical frameworks, which only skim the surface of ecosystems without exploring deeper, implicit connections, fail to combine theoretical paradigms of firms (such as their roles or functions) with empirical evidence from companies in the ecosystem. This disconnect leaves decision-makers with incomplete views of their competitive landscape, obscuring critical insights through blind spots that could create or break their strategies [1, 2].

These blind spots persist because, despite the increasing complexity of ecosystems [3, 4], existing frameworks within the literature remain limited in capturing the full complexity of ecosystem structure. Current literature approaches this complexity through two distinct streams: (1) conceptual [5, 6, 3] or mathematical models [7] that lack explicit empirical integration, and informal extensions to these [8], and (2) data-driven [9], syntactic network models [10, 11, 4] that map direct relationships between ecosystem stakeholders but fail to capture deeper, implicit connections. The fundamental shortcoming

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of these approaches is their inability to bridge theory and evidence, which results in a gap. This gap creates analytical blind spots for strategic analysts, obscuring implicit yet strategically significant connections among ecosystem stakeholders and limiting the organization's capability to comprehend their competitive arena and make informed strategic decisions.

Therefore, to fill this gap, an extension of the business ecosystem analysis frameworks is needed. This new approach should move beyond syntactic to semantic understanding by shifting from purely structural network relationships (syntactic) [10, 11, 4] to meaningful models that also capture and integrate the domain knowledge (semantics), effectively amalgamating theory with empirical evidence. Hence, the authors asked;

*How can we extend the business ecosystem frameworks to effectively bridge evidence and theory to derive meaningful representations for strategic analysts in complex business ecosystems?*

To address the limitations of conventional approaches in capturing semantic relationships, we introduced the Business Ecosystem Analysis & Representation (BEAR) framework [12], which formally integrates theoretical concepts with empirical evidence. Furthermore, to demonstrate BEAR's practical value, we implemented BEAR through a collaboration with an incumbent manufacturer within the wind energy ecosystem, formulating a specific conceptual question about organizational positioning and supply chain dynamics. To answer this question, we collected and analyzed data from companies at WindEnergy Hamburg 2024 [13]. By learning how these semantic relationships occur within real business contexts, we contribute to the theoretical understanding of business ecosystem structures and practical tools such as our knowledge graph for strategic analysts facing complex interdependencies.

## 2. Related Work

BEAR's semantic approach is fundamentally grounded in dynamic ontological modeling that draws on philosophical critiques of static formalization [14, 15]. Inspired by Wittgenstein's later work [14], which emphasizes language as a contextual problem-solving tool — where meaning emerges from use — we treat ontologies as evolving approximations rather than fixed theoretical models. This perspective aligns with Whitehead's process philosophy [16], which favors adaptive representations over rigid abstractions. Scholars following similar paradigms have significantly influenced our framework [15, 17] while contrasting approaches prioritizing logical consistency over adaptability have helped refine our position [18]. Although iterative empirical validation across different contexts (e.g., different business ecosystems) remains necessary to validate our framework [19], these philosophical foundations and other scholarly works strengthen our framework's foundations.

BEAR methodologically integrates design science principles, particularly the works of Roel J. Wieringa [19], which demonstrates how guiding questions can iteratively refine our theoretical understanding of the domain and its problems. This iterative process reflects Peircian fallibilism [17], allowing the framework to update its ontological assertions when new data falsifies or refines prior versions. Unlike earlier business ecosystem frameworks [10, 11, 4, 3], BEAR embraces the fallibalistic stance [17]and focuses on pragmatic utility to better support strategic analysts.

## 3. Business Ecosystem Analysis & Representation (BEAR)

To fill the aforementioned gap, we propose a formal and adaptive framework for business ecosystem analysis that integrates dynamic ontology and knowledge graph development with semantic-driven network visualizations. Additionally, the framework incorporates a pragmatic, question-based feedback mechanism to facilitate continuous improvement (see Figure 1).

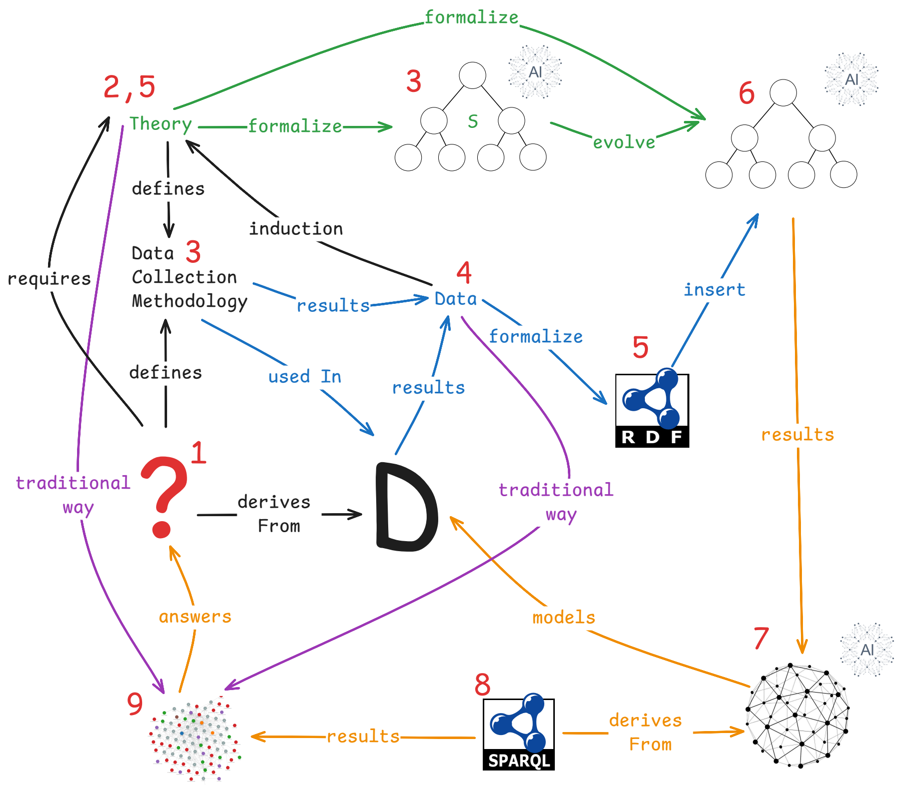


**Figure 1:** This conceptual overview of the BEAR framework represents how the process begins with a guiding question and concludes with a visualization. The numbers indicate the logical path, while the color-coding distinguishes different paradigms within our framework: blue signifies the data-driven approach, green represents the theoretical approach, orange indicates the amalgamation of both, and purple denotes the traditional methods commonly found in the literature [10, 11, 4, 6].

### 3.1. Question & Domain of Interest

We begin by formulating guiding questions (see Number 1 in Figure 1) within our framework to ensure focused and meaningful evidence collection and analysis. These questions should either improve theoretical understanding or solve pragmatic problems, fundamentally shaping the scope of our inquiry within the domain of interest. This shaped scope of inquiry, directed by the guiding question, acts as the primer for our framework, guiding which aspects of the domain are explored, modeled, and ultimately visualized, drawing inspiration from design science research [19].

In addition to this question's scope-defining property, we consider it a catalyst for framework evolution, transitioning it from one state of knowledge about the domain of interest to the next as new questions are generated from it.

### 3.2. Business Ecosystem Ontology (BEO)

Our framework incorporates an explicitly defined a-priori ontology (see Number 2 in Figure 1) as a foundational element to effectively answer the questions, driving framework evolution. This "seed" ontology is not merely a structural component but a critical catalyst, enabling key functions within our framework. Firstly, it provides an explicit foundation for data collection and ensures the seamless integration of a theory-driven paradigm. This functionality directly enhances the framework's adaptability by the possibility of generating new states of knowledge as inquiry progresses. Secondly, employing such ontology explicitly acknowledges that every scientific or pragmatic question embodies a theoretical perspective on the domain. This recognition is crucial for grounding our framework, which makes it trackable from its initial conceptualization.

Also, a computational approach is demanding because of the complexity and dynamism inherent in business ecosystems [4]. To address this computational demand and enable automated analysis, we formalized our ontologies using the Web Ontology Language 2 (OWL2) [20]. With OWL2, while we may sacrifice some of the nuanced expressiveness of natural language, this formalization process is a deliberate trade-off. This trade-off enables us to leverage the power of automated deductive reasoning through symbolic artificial intelligence—OWL 2 DL reasoners [20]—a crucial technology for analyzing complex semantic systems.

### 3.3. Data & Data Collection Methodology

We treat data as fundamental units of ecosystem theory [21] to ground our business ecosystem framework in empirical evidence and extend our domain understanding. Therefore, data acquisition from the domain of interest must transition from a passive activity to a structured and theory-driven process, ensuring relevance and coherence within our framework.

### 3.4. Knowledge Graph

The knowledge graph is the core model for achieving a deeper semantic understanding of the business ecosystems within our framework (See Number 7 in Figure 1). This approach moves beyond primary syntactic analysis, which is limited by its focus on mere word processing [4]. Instead, our approach with knowledge graphs enables us to grasp the implicit (underlying) meaning and relationships between ecosystem concepts. We define these knowledge graphs as integrated representations that combine data with our ontological theory, effectively capturing and modeling the domain of interest in a structured manner.

### 3.5. Ontology and Knowledge Graph Development

We selected Protégé as our primary ontology prototyping tool [20] to develop the ontologies and subsequent knowledge graphs for business ecosystems. Pragmatic factors drove this decision to select Protégé. These factors [20] included Protégé's open-source nature, robust reasoner integration for practical deductive reasoning, and extensive extension suite, making it an efficient and practical choice for our development needs.

### 3.6. Query

To effectively query the developed formal knowledge graphs and retrieve answers relevant to our questions, we utilize SPARQL [20] as our query language. For the execution of SPARQL, we utilize Apache Fuseki Server. Subsequently, to manage the data structure resulting from this execution, we use JSON-LD within our framework.

### 3.7. Business Ecosystem Visualizer (BEV)

We developed a dedicated Business Ecosystem Visualizer (BEV) [22], to effectively answer the question by revealing implicit insights within the business ecosystem, leveraging the rich semantic information gathered through our knowledge graph. We specifically designed this semantic-driven visualization software to generate network visualizations driven by semantics, going beyond pure structural representations. Furthermore, by integrating semantic information from the knowledge graph, our visualizer aims to unlock a richer understanding of ecosystem dynamics and relationships.

# 4. Results of the Application of BEAR to Wind Energy Ecosystem

In this section, we revealed how BEAR effectively uncovered hidden insights within the complex wind energy ecosystem. To guide the reader through this discovery process, we detailed a logical path undertaken by BEAR, from our initial question to the final insightful visualization generated with BEV.

To effectively analyze the dynamics of the wind energy ecosystem, we began by formulating guiding questions as the role of strategic analyst. This process involved collaborative video meetings with three key managers from a leading incumbent manufacturer: a business development manager, an innovation manager, and a digital business manager. Their insights ensured that our questions were practically relevant and theoretically significant, contributing to the advancement of business ecosystem analysis. A representative question that guided the BEAR was:

*How do specific companies establish their positions through product&service delivery interactions within the wind energy ecosystem?*

Even though a sampled question inherently introduces a limitation of this paper, as the complete set of questions would undoubtedly provide a much deeper and richer understanding of the domain, this representative question effectively served as a starting point for our framework. However, to enable readers to gain a fuller perspective and facilitate further investigations, we provide an anonymized dataset, and our data collection methodology is publicly available on our GitHub page [12].

## 4.1. Building the Foundation: A Seed Ontology for Wind Energy

Based on our guided question, we began by developing a foundational seed ontology. While recognizing the potential benefits of automated approaches, we manually extracted implicit and explicit core concepts and their relationships. Later, we formalized these using OWL2 [20], which resulted in an explicit seed ontology including two classes—Company and Organization—and two fundamental relation types—deliversTo and receivesFrom. This initial ontological structure served as a foundation for understanding the wind energy ecosystem, directly addressing our guiding question.

**Table 1**
Mapping of Natural Language to OWL2 Formalization

| Natural Language | OWL2 Formalization |
|---|---|
| Company | <owl:Class rdf:about="https://purl.org/beo#Company"><br><rdfs:subClassOf rdf:resource="https://purl.org/beo#Organization"/><br></owl:Class> |
| Delivers to | <owl:ObjectProperty rdf:about="https://purl.org/beo#deliversTo"><br><rdfs:subPropertyOf rdf:resource="http://www.w3.org/2002/07/owl#topObjectProperty"/><br><owl:inverseOf rdf:resource="https://purl.org/beo#receivesFrom"/><br></owl:ObjectProperty> |

## 4.2. Collecting Empirical Evidence: Surveying at WindEnergy Hamburg 2024

To gather evidence for the concepts derived through our seed ontology, we strategically chose WindEnergy Hamburg 2024 [13], one of the largest wind energy expositions, as our data collection area. This event provided an opportunity to engage directly with a broad spectrum of wind energy organizations. Even though further details about our survey methodology will be provided in a future publication (See GitHub page for the survey [12]), our survey efforts resulted in a robust 32% participation rate. Of the

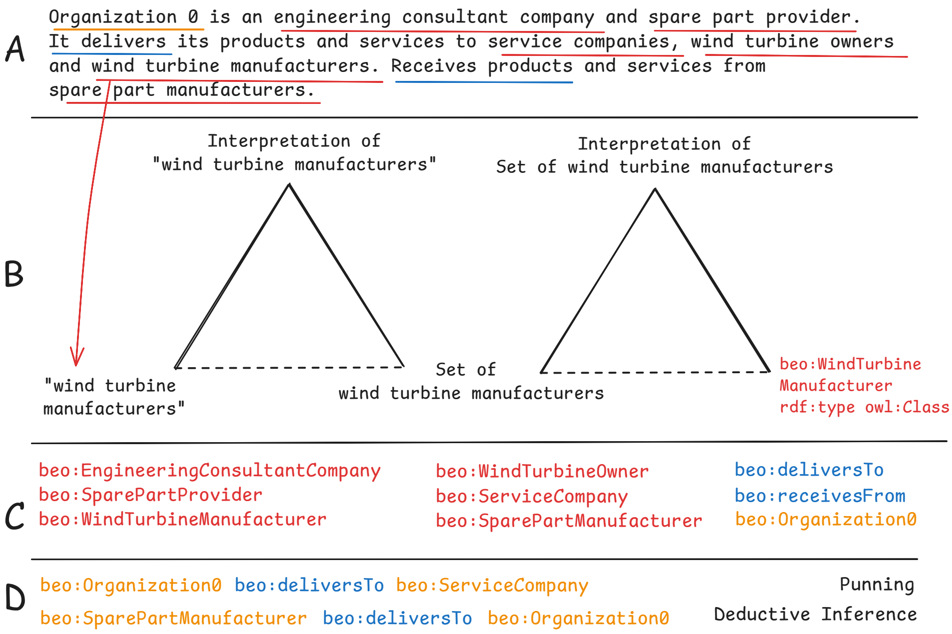


**Figure 2:** We divided the figure into parts A, B, C, and D, illustrating the formalization of *symbols* derived from data collected from an anonymized organization, referred to as Organization 0. In this visualization, symbols such as *Organization0* are denoted with underlines or distinct color codes: orange highlights individual companies, red designates sets of companies, and blue marks the relationships, which are depicted in parts A and C. Part B represents our interpretation of these symbols through Peircian semiotic theory [23], with a semiotic triangle [24] illustrating the case of the symbol *wind turbine manufacturers*. Finally, part D presents the punning technique informally, leveraging color-coding by representing classes as individuals, and one example of techniques resulting in necessary deductive inference.

120 organizations we approached at the exposition, 35 actively participated, contributing to 37 valuable survey responses, with two responses originating from the same company.

### 4.3. Inductive Expansion and Deductive Inference: Evolving the Ontology

Building upon the survey evidence, we significantly expanded our seed ontology to represent the wind energy domain. This expansion process, leveraging semiotic interpretations (See Figure 2) of survey responses, significantly grew the ontology. Specifically, we inserted 134 new classes, each with varying levels of granularity.

To further enhance the ontology's capabilities, we employed punning [20] within the OWL2. This technique allowed us to treat key concepts in our ontology, simultaneously representing them as individuals using the same Internationalized Resource Identifier (IRI) [20]. As a result of this technique, our ontology reinforced the indented semantics with a more robust structure. More crucially, punning also unlocked the reasoning abilities within the ontology, enabling us to perform more sophisticated automated checks and deductions, leading to a more reliable and insightful knowledge graph (See Figure 2.

### 4.4. Knowledge Graph: Theory and Evidence into a Unified Model

After integrating all survey data and the expanded ontology, a knowledge graph integrating theory and evidence emerged. Even though punning blurred the borders, the T-box (terminological component) provided the theoretical business ecosystem understanding. On the other hand, the A-box (assertional component) contained the evidence gathered from WindEnergy Hamburg, grounding our T-box assertions in empirical data. Consequently, the resulting knowledge graph offered a holistic and semantically rich ecosystem model, surpassing the sum of its parts. Finally, with all its inferred assertions, this knowledge graph was saved and uploaded to a Fuseki server, ready for querying.

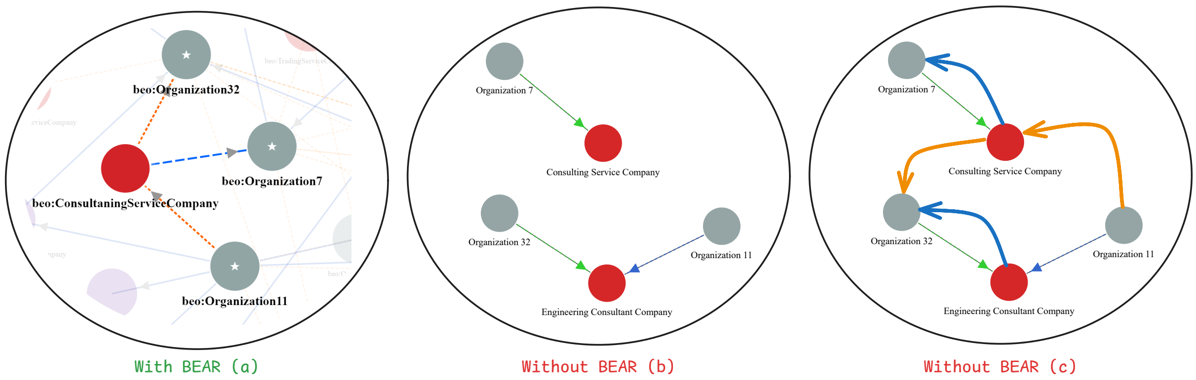


**Figure 3:** Subgraph visualizations show the wind energy ecosystem segment with a comparative analysis of implementations with and without the BEAR framework. This visualization maps organizational positioning and supply chain relationships based on products and services. Dashed orange lines represent meta-reasoning inferred relationships; blue dashed lines represent combined inference and knowledge graph assertions (a), and green dashed lines (b) denote specifically "receivesfrom" relationships. Solid blue and orange lines in the non-BEAR implementation (c) highlight the reasons for structural sparsity, demonstrating the framework's capability to reveal hidden ecosystem dependencies.

### 4.5. Extracting answers from Knowledge Graph

To answer our initial guiding question, we moved beyond simple knowledge graph visualization and formulated two SPARQL queries with specific purposes [12]. The first query aimed to capture the theoretical structure by targeting the T-box, while the second query focused on the A-box to analyze the enriched data through deductive inference.

Executing both queries on the Fuseki server and saving the results in JSON-LD format enabled seamless integration with our BEV, ensuring a direct pathway from guiding question to answer. For transparency and reproducibility, both SPARQL queries are available in our GitHub repository [12].

### 4.6. Meta-Reasoning: Overcoming OWL2 DL Inference Limitations

In our wind energy knowledge graph analysis, we encountered a limitation in standard OWL2 DL reasoners [20] when processing punned classes. While punning effectively linked our ontology's classes and individuals, the reasoners failed to infer subclass inheritance between the class types. For example, if "WindTurbineManufacturer" is a subclass of "Manufacturer" and both are pruned, the reasoner could not deduce that any property which is asserted to WindTurbineManufacturer also true for the Manufacturer.

We tested this behavior further by applying property chains to chain the subclass with object properties, but OWL2 DL does not support such inferences, unlike the OWL2 RL profile [20]. To address this limitation, we developed a custom script (available on our GitHub page) that manually infers subclass inheritance for punned classes. Additionally, we explored the use of the OWL2 RL profile, which supports the necessary inferences, which can be seen in our Python tests (also available on GitHub [12]).

### 4.7. Answering the question: Wind Energy Ecosystem Visualization

Using our BEV [22], we transformed the query results into intuitive network visualizations that reveal complex relationships within the wind energy ecosystem (See Figure 1). Unlike traditional visualizations that focus solely on direct connections, BEV incorporated inferred relationships—such as emerged intermediary roles (See Figure 3) between the organizations—and varying levels of granularity derived from the BEAR framework.

Even though we will provide explicit details on the development process of our visualization system in a future publication, it evidently (See Figure 3) extends traditional business ecosystem visualizations by incorporating inferred relationships and varying levels of granularity derived from the embedded theory.

## 5. Discussion

Conventional business ecosystem analysis frameworks often fail to capture the complex relationships that define business ecosystems. This limitation, particularly their tendency to overlook implicit connections and deeper semantic meanings, as highlighted in our introduction, can lead to significant consequences, such as missed strategic insights [3, 4]. The BEAR framework (See Figure 1) directly addresses these limitations by bridging the gap between the theory and empirical data through precise semantic representation.

A critical contribution of the BEAR lies in its semantic precision for network-driven analysis. Traditional network-driven ecosystem analysis often fails to consider data semantics [10, 11, 4], which could lead to significant misinterpretations. For example, consider the statement, "Gearbox manufacturer AG (the company from which we gathered data) is delivering to wind turbine manufacturer." Without semantic understanding, "wind turbine manufacturer" could be interpreted as referring either to a specific company that manufactures wind turbines or the entire set of wind turbine manufacturers. Treating these semantically distinct relationships as equivalent in a network analysis can result in misapplied graph-theoretic measures (such as centrality), ultimately leading to flawed insights that misinform strategic decision-making.

To overcome these semantic misinterpretations, BEAR introduces a refined approach to relationship modeling, interpreting the connections as quantified relationships between the sets and members of the set rather than mere links. This suggested perspective, partially enabled by the OWL2 DL's capabilities [20], allows BEAR to distinguish between fundamentally different types of relationships beyond basic network relationships. For example, consider the same statement above. Traditional approaches might treat this "delivery" as a simple link. However, BEAR interprets this relationship as existential quantification: "There exists at least one wind turbine manufacturer to whom Gearbox manufacturer AG delivers," even if we cannot identify the specific receiver. By explicitly modeling such relationships as existential quantifications, BEAR achieves a semantic precision previously absent in business ecosystem literature to our knowledge, offering a more accurate and insightful representation of complex interdependencies.

Beyond simply preventing semantic misinterpretations, BEAR's semantic awareness, combined with consideration of granular ecosystem levels, introduces a more profound benefit: uncovering implicit ecosystem dynamics. This capability allows strategic analysts to see beyond surface-level connections and uncover crucial yet hidden interdependencies. For example, in our analysis, leveraging BEAR, we uncovered the intermediary role of consulting companies between certain organizations(See Figure 3), a dynamic that would remain hidden in traditional analyses. This underscores the neccesity of our discussion and the paradigm of BEAR: reasoned and synergistic amalgamation of theoretical frameworks with rich empirical evidence.

While some approaches rely only on natural language processing (NLP) for inductive analysis [4], this often results in what John Sowa termed a "knowledge soup" - a disorganized and opaque mass of information lacking clear structure or meaning [25]. Instead of cooking this knowledge soup, our BEAR framework leverages formally defined ontologies to provide a backbone, creating meaningful and transparent knowledge structures. However, we acknowledge the initial labor involved in our approach. Therefore, rather than rejecting the NLP techniques [4] and Large Language Models, we view them as valuable assistants in our future efforts to semi-automate this labor-intensive process.

Beyond its semantic precision in data representation, another aspect of BEAR is its visualization capabilities. Visualizing relationships with quantifications presents significant challenges and needs further research [26]. However, through BEV [22], we aim to overcome this limitation by capturing the semantics of business ecosystem relationships by implementing distinct interaction types. In this work, we introduced two such types — extending the current business ecosystem visualization literature, where such semantics distinctions are not typically present:

1. Some company within a set delivers to a specific company
2. A specific company delivers to some company within a set

These distinctions enable strategic analysts to interpret complex relationship patterns with greater semantic accuracy, exceeding conventional visualization approaches [4, 11], leading to deeper and more insightful ecosystem understanding.

An additional advantage of our framework emerges from its foundation in semantic web technologies, making BEAR inherently suitable for integration with other domain ontologies such as SWOTONT [27]. This capability opens up the possibility of conducting a SWOT analysis directly within the business ecosystem analysis, which demonstrates BEAR's adaptability for addressing diverse analytical questions spanning multiple business analysis domains.

## 6. Conclusion

The Business Ecosystem Analysis and Representation Framework (BEAR) advances traditional business ecosystem analysis by directly addressing a critical challenge: the inherent complexity that hides insightful ecosystem dynamics [4, 3, 1]. BEAR addresses this challenge by bridging theoretical assertions with empirical evidence through a semantic approach. When utilized in the wind energy ecosystem, this semantic approach unlocked previously hidden insights, revealing relationships that conventional methodologies would miss. Therefore, by revealing these hidden insights and formalizing complex relationships, BEAR [12]demonstrates a more accurate and transparent foundation for strategic analysis, offering organizations an advantage.

As organizations increasingly recognize the complexity of their ecosystems [4, 3], BEAR emerges as the analytical structure needed to avoid ecosystem blind spots [1], particularly those important yet hidden dependencies. Furthermore, BEAR transforms complex ecosystems into sources of sustainable competitive advantage. This capability ultimately empowers organizations not only to survive but also to thrive, dynamically adapt, and succeed within their dynamic business ecosystems.

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## Declaration on Generative AI

While preparing this work, the author(s) used GROK-3 Beta, OpenAI o3-mini, DeepSeek R1 671B, and Grammarly to perform grammar and spelling checks. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

## References

[1] E. J. Zajac, M. H. Bazerman, Blind spots in industry and competitor analysis: Implications of interfirm (mis)perceptions for strategic decisions, The Academy of Management Review 16 (1991) 37–56. URL: http://www.jstor.org/stable/258606.

[2] J. F. Moore, Business ecosystems and the view from the firm, The antitrust bulletin 51 (2006).

[3] M. G. Jacobides, C. Cennamo, A. Gawer, Towards a theory of ecosystems, Strategic management journal 39 (2018) 2255–2276.

[4] R. C. Basole, H. Park, C. D. Seuss, Complex business ecosystem intelligence using ai-powered visual analytics, Decision Support Systems 178 (2024) 114133. doi:https://doi.org/10.1016/j.dss.2023.114133.

[5] C. H. Tian, B. K. Ray, J. Lee, R. Cao, W. Ding, Beam: A framework for business ecosystem analysis and modeling, IBM Systems Journal 47 (2008) 101–114. doi:10.1147/sj.471.0101.

[6] S. Rinkinen, V. Harmaakorpi, The business ecosystem concept in innovation policy context: building a conceptual framework, Innovation: The European Journal of Social Science Research 31 (2018) 333–349. doi:10.1080/13511610.2017.1300089.

[7] Z. Ma, Business ecosystem modeling- the hybrid of system modeling and ecological modeling: an application of the smart grid, Energy Informatics 2 (2019) 35. doi:10.1186/s42162-019-0100-4.

[8] K. Rong, G. Hu, Y. Lin, Y. Shi, L. Guo, Understanding business ecosystem using a 6c framework in internet-of-things-based sectors, International Journal of Production Economics 159 (2015) 41–55. doi:https://doi.org/10.1016/j.ijpe.2014.09.003.

[9] H. Jodlbauer, S. Tripathi, N. Bachmann, M. Brunner, Unlocking hidden market segments: A data-driven approach exemplified by the electric vehicle market, Expert Systems with Applications 254 (2024) 124331. doi:https://doi.org/10.1016/j.eswa.2024.124331.

[10] R. Basole, M. Russell, J. Huhtamäki, N. Rubens, K. Still, H. Park, Understanding business ecosystem dynamics: A data-driven approach, ACM Transactions on Management Information Systems 6 (2015). doi:10.1145/2724730.

[11] R. C. Basole, T. Clear, M. Hu, H. Mehrotra, J. Stasko, Understanding interfirm relationships in business ecosystems with interactive visualization, IEEE Transactions on Visualization and Computer Graphics 19 (2013) 2526–2535. doi:10.1109/TVCG.2013.209.

[12] A. Tüzün, BEAR, 2025. URL: https://github.com/T-Z-N/BEAR.

[13] WindEnergy Hamburg, Global on & offshore event, 2024. URL: https://www.windenergyhamburg.de/, [Online; accessed 2025-03-14].

[14] L. Wittgenstein, Philosophical investigations, 2019.

[15] J. F. Sowa, A dynamic theory of ontology, FRONTIERS IN ARTIFICIAL INTELLIGENCE AND APPLICATIONS 150 (2006) 204.

[16] A. N. Whitehead, Process and reality, Simon and Schuster, 2010.

[17] M. K. Bergman, M. K. Bergman, Lagerstrom-Fife, Knowledge Representation Practionary, Springer, 2018.

[18] B. Smith, Ontology, in: G. Hurtado, O. Nudler (Eds.), The Furniture of the World: Essays in Ontology and Metaphysics, Editions Rodopi, 2012.

[19] R. J. Wieringa, Design Science Methodology for Information Systems and Software Engineering, 1 ed., Springer Berlin, Heidelberg, 2014. doi:10.1007/978-3-662-43839-8.

[20] P. Hitzler, M. Krötzsch, B. Parsia, P. F. Patel-Schneider, S. Rudolph, et al., Owl 2 web ontology language primer, W3C recommendation 27 (2009) 123.

[21] G. H. Mealy, Another look at data, in: Proceedings of the November 14-16, 1967, fall joint computer conference, 1967, pp. 525–534.

[22] A. Tüzün, BEV, 2025. URL: https://github.com/T-Z-N/BEV.

[23] A. Atkin, Peirce's Theory of Signs, in: E. N. Zalta, U. Nodelman (Eds.), The Stanford Encyclopedia of Philosophy, spring 2023 ed., Metaphysics Research Lab, Stanford University, 2023.

[24] C. K. Ogden, I. A. Richards, The meaning of meaning: A study of the influence of thought and of the science of symbolism (1923).

[25] J. F. Sowa, The challenge of knowledge soup, Research trends in science, technology and mathematics education (2006) 55–90.

[26] A. Moktefi, A.-V. Pietarinen, On the diagrammatic representation of existential statements with venn diagrams, Journal of Logic, Language and Information 24 (2015) 361–374.

[27] A. Tüzün, S. Tripathi, N. Bachmann, A.-K. Thienemann, M. Brunner, H. Jodlbauer, Granular and relational swot analysis: An ontological approach, Procedia Computer Science 253 (2025) 2575–2585. doi:https://doi.org/10.1016/j.procs.2025.01.317.