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Big Data Guided Supply Chains and Interpretation of Value-Added Knowledge within Coexistent Logistic Ecosystems

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Abstract

Supply chains are frequently disrupted by human and environmental factors, which can significantly impact human lifestyles and economic conditions, particularly evident during the recent pandemic. This research aims to explore the connections between supply chain events and to understand the importance of human activities and environmental challenges in logistics and supply chain operations. The consequences of these disruptions often include economic costs and effects on human well-being. The study envisions a coexistence among various ecological systems that can help sustain supply chains while providing valuable insights into these ecosystems. Digital ecosystems and technologies (DEST) are critical tools for establishing connections and understanding the coexistence of different ecological systems. For instance, big data-driven supply chains illustrate the sustainability and operational effectiveness of information system (IS) artefacts. By linking supply chain events, this approach ensures that integrated projects deliver quality products and services to valued customers.

Keywords: Big Data, Supply Chains, Integrated Project Management (IPM), Coexistent Digital Ecosystems, Extracting values, Knowledge Interpretation.

What is the LSCE construct design, and its relationship with the coexistent HHEE ecological construct?

We present a concept of ecosystem as an actionable framework that coexists with various ecologies, as Adner (2017) described. Logistics and supply chains (LSC) are spatial in nature and are influenced by human, environmental, and economic ecosystem (HHEE) constraints. In our research, we utilize data sources connected to these ecosystems, interpreting them within spatial contexts. This often involves working with Big Data, which can be structured, semi-structured, or unstructured (Sivarajah et al., 2016; Nimmagadda et al., 2019b). Such data can be heterogeneous, multidimensional, and multidirectional, mainly when analyzed across logistics routes, supply chains, and transport trajectories. In this study, we aim to understand how ecosystems affect each other by establishing the interconnectivity between various data systems and addressing the challenges faced by consumer products and relevant ecosystem service providers. In the subsequent sections, we will elaborate on integrating Big Data with ecosystem design concepts. Logistics and supply chains can indirectly affect human and environmental health, but they directly impact businesses, as illustrated in Figure 1. In other words, for successful LSC operations, human and environmental conditions must be conducive to achieving corresponding business or economic objectives. The connectivity phenomena are conceptualized as depicted in Figure 1.

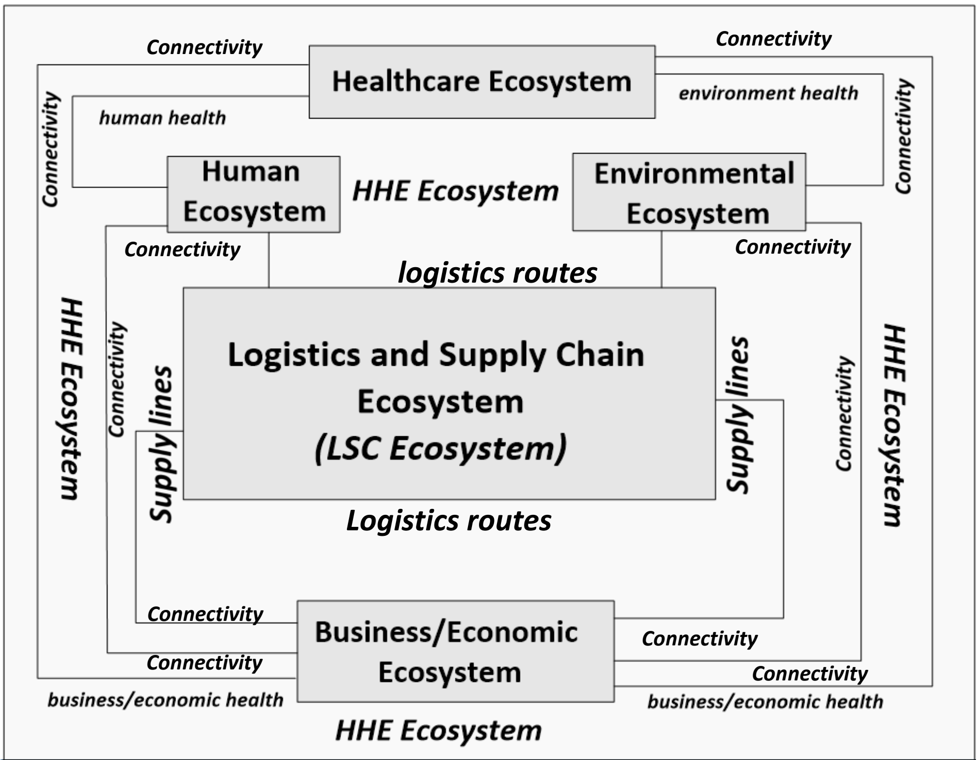

Figure 1: Relationships between LSC and HHEE ecosystem (construct) communities

Purpose of Collaborative Big Data guided Logistics and Supply Chain Ecosystem (LSCE) Construct Design

A collaborative ecosystem facilitates the exploration of information system designs that connect ecological data, verify factual instances, and manage knowledge and file information. For example, the relationship between two ecological communities, the LSC and HHEE ecosystems, illustrates this collaborative existence, as shown in Figure 1. Tools such as shared whiteboards, distributed or parallel computing engines, and coordinated data search agents can efficiently manage ecologically controlled management information systems on a large scale. For instance, events L1 and S1 from the LSCE construct can be connected to events H1, H2, E2, and E3 from the HHEE construct. Multiple ecosystems necessitate multidimensional data sources crucial in unifying and balancing ecological networks. Multidisciplinary data are essential for digitally fusing and mapping information within a holistic, integrated framework theorization process (Nimmagadda et al. 2019b).

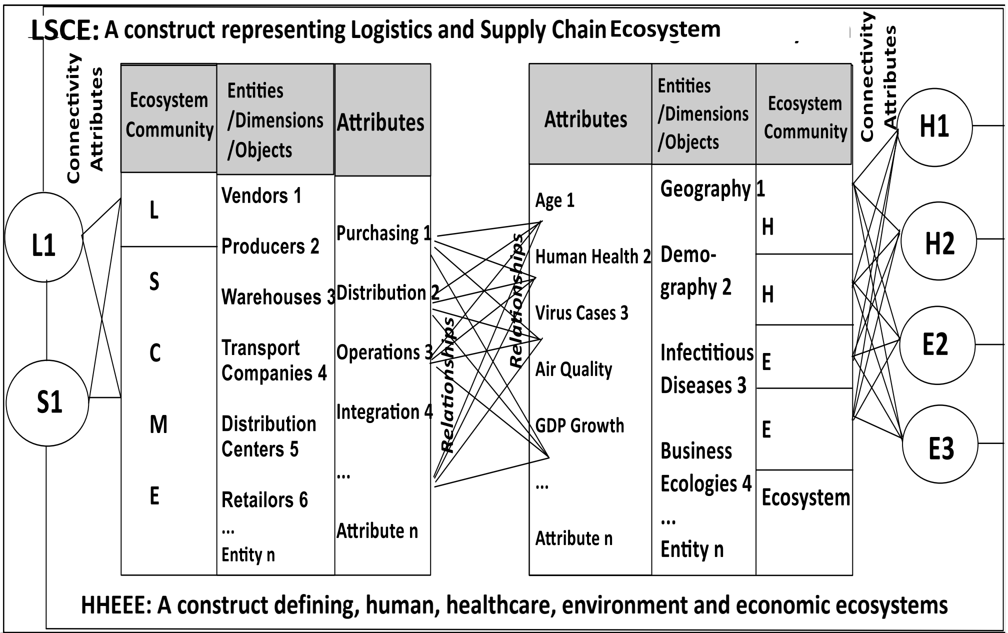

Figure 2: A schematic view of analysing relationships between various digital ecosystems

The research design evaluates data schemas derived from Big Data systems and applies interpretative analyses of domain knowledge on an ecosystem scale. To identify data patterns and insights in ecosystems, Big Data tools examine the implications of implementations across various ecological contexts (Cleary et al., 2012). Unstructured data, often found in text files, accounts for 80% of an organization's total data volume. When the sheer volume and variety of data become unmanageable, it can lead to significant costs for enterprises. Additionally, maintaining the annual storage of unstructured data can be expensive. In Figure 2, we interpret the connectivity between coexisting systems by identifying their respective data relationships, leading us into the mapping and modelling stages. High-speed computing services, such as MapReduce from the Hadoop framework, utilize multiple distributed servers to provide ecosystem services on a global scale (Ajibade and Adediran, 2016). Big Data analytics can uncover hidden patterns and unknown correlations within multidisciplinary ecological datasets, allowing organizations to discover valuable new information, enhance marketing strategies, and increase revenues. Data cube views, interpreted through mining algebra, yield new insights and valuable knowledge across multiple ecosystems. Big Data tools, including Business Intelligence (BI) programs, are used to assist ecosystem service providers in making informed technical and business decisions, as explained by Nimmagadda (2015).

Sensor technologies can enhance services and streamline transaction logging in geographically diverse ecosystems. In current research, big data analytics utilizes software tools for predictive analytics and statistical data mining, as highlighted by Premalatha and Baskar (2012) and Shirkhorshidi et al. (2014). The diversity and complexity of unstructured and fragmented ecosystems drive the need for multidimensional data sources better suited for analysis through big data analytics. Traditional databases often struggle with data integration due to the limitations of repository system designs. These challenges highlight the necessity for additional big data analytics initiatives requiring skilled IT professionals with advanced analytical expertise. With the growing demand for integrating Hadoop systems and big data warehouse solutions, the authors discuss various software solutions, interfacing technologies, and integrated frameworks for data science and design-science-guided information systems (DSIS). Marchet et al. (2018) and Nimmagadda et al. (2021) present several integrated frameworks that can drive innovations in data visualization and mining, thereby facilitating new knowledge discovery. The DSIS framework can help interpret data views derived from metadata that fuse the Logistics and Supply Chain (LSC) ecosystem with Human-Health-Environment-Economic (HHEE) ecological communities.

Data sources that belong to multiple ecosystems play a vital role in unifying and balancing ecological networks. Multidisciplinary data sources are essential for digitally integrating and mapping these ecosystems through a holistic framework. This research explores the interplay and collaboration between big data systems and digital ecologies. Business rules and constraints can significantly impact ecosystem relationships and their representations during data integration and digital collaborations. To address these challenges, the authors present a new architectural schematic for mapping and modelling various attribute dimensions in decision-support evaluable spaces. The mapping and modelling may be derived from the HHEEE (Human, Health, Environment, Economy) community contexts or integrated metadata views, as illustrated in Figure 1. For instance, the LSCE (Logistics Supply Chain Ecosystem), which motivates Integrated Project Management (IPM), relies on metadata derived from the HES (Human), HEAL (Healthcare), ENV (Environmental), and ECON (Economic) schemas, with an emphasis on multidimensional ontologies. Figure 3 depicts several schemas with various conceptualized attributes such as "govern, regulate, control and manage" to interconnect the LSC (Logistics Supply Chain) and HHEE ecologies. The HES, HEAL, ENV, and ECON schemas collectively serve as a framework through which various attribute dimensions and factual instances are interconnected, supported by detailed mapping and modelling relationship tables.

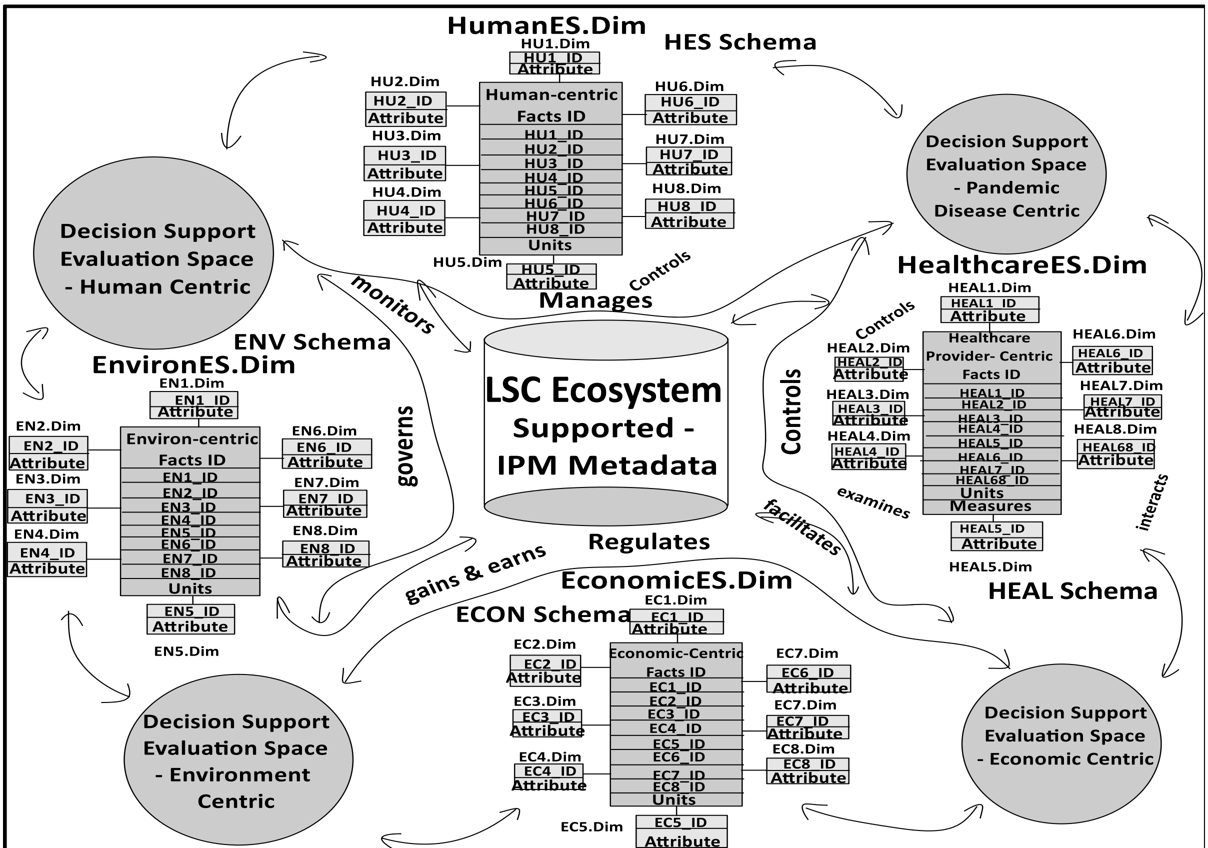

Figure 3: Schematic architecture – interplay between data schemas to support the LSC Ecosystem

Metadata is used during data mining and visualization to construe new ecological insights, as discussed in the following sections.

Findings of Data Mining, Fusion, Visualization and Interpretation

Data mining involves the exploration of correlations, trends, and patterns within ecosystem metadata. Various rules and processing programs for business operations are documented in the literature (Pujari, 2001; Vatsavai et al., 2012). Techniques such as slicing and dicing are commonly used to manage multidimensional data cubes. Additionally, as Castanedo (2013) discussed, data fusion combines multiple datasets to uncover knowledge about data patterns and create consistent, accurate, and interpretable representations of real-world entities, dimensions, and objects from coexisting ecosystem metadata. Moreover, metadata cubes can extract valuable data views using statistical mining, SQL queries, and mapping tools that produce graphical representations. Map views illustrate the contours of various attributes interpreted within the LSC-HHEE ecosystem community, as shown in Figures 4a and 4b. Each contour represents a line connecting points of equal attribute value between two variables, which can belong to either of the ecosystem communities. For instance, the LSC ecosystems can be linked with the HHEE ecosystems in the spatial domain, as portrayed in Figure 4. Integrating ecological data results in a more effective digital classifier than other classifiers relying on individual dimensions and unified representations (Yen et al., 2019). The associated ecosystems combine human, healthcare, environmental, and economic domains. Researchers can investigate different ecological interactions and attribute relationships among LSC-HHEE ecosystem communities by integrating data from various sources. While the attributes and instances of ecosystem data are consolidated through data fusion, a similar approach is applied when handling multiple data cubes fused into a holistic cuboid data schema. These schemas can interface with the DSIS framework and its metadata. This procedure enables ecosystem providers to gain new insights through interactions between coexisting ecosystems as represented by cuboid data fusion views. Fusion technology plays a crucial role in processing and presenting data visualizations that enhance our understanding of diverse ecological insights, thereby adding value to the interpretive process expected by ecological researchers.

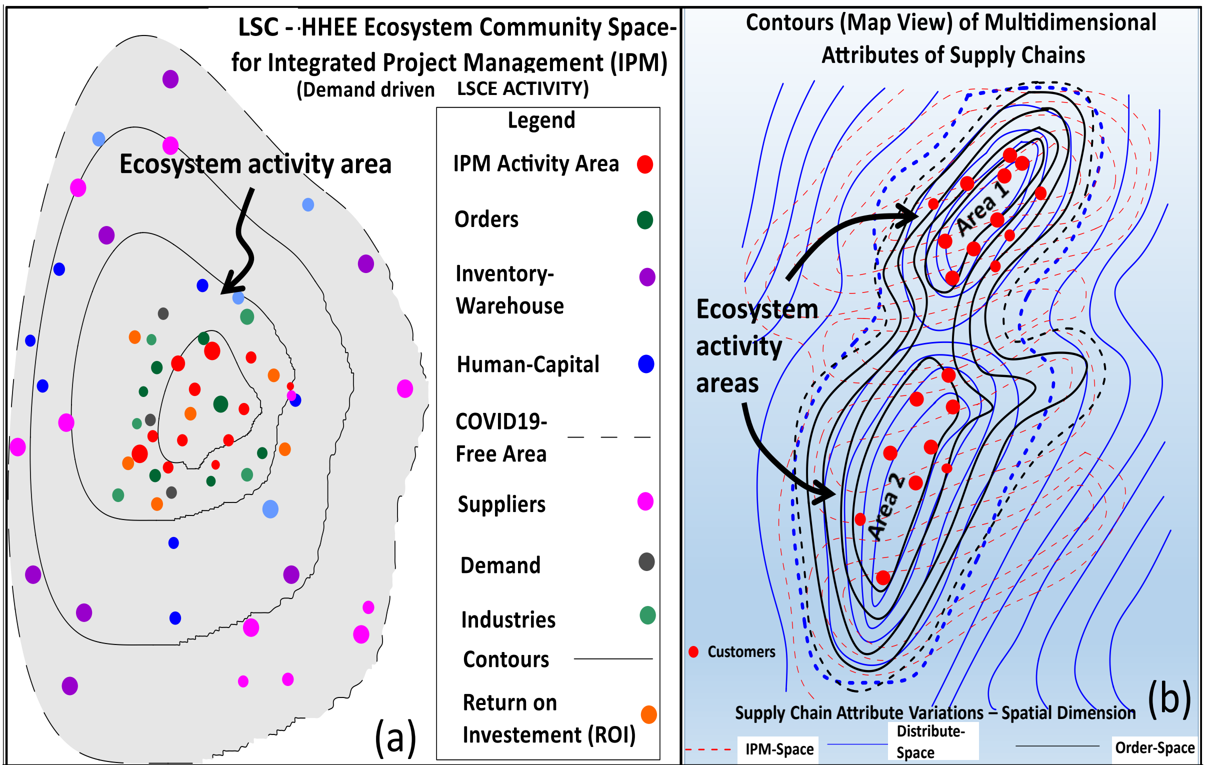

Figure 4: (a) Mapping and modelling data views - assimilating value-added knowledge of LSCE community (b) Contoured map view of supply chain attributes

In the current research, the authors describe digital ecology mapping combined with data fusion, which allows for creating integrated narratives and multidimensional visualizations or map views for investigative ecologies. This method is beneficial for analyzing digital ecosystems and new knowledge domains. The supply chain system's elements and associated datasets are merged into a fused dataset, enabling various applications to work across different fields. For instance, human, health, environment, and economic (HHEE) ecosystems influence logistics and supply chain ecosystems while merging the entities and attributes of each component and their corresponding data tables into a unified framework.

The data instances within these conceptual chains can maintain the integrity of the original ecological facts and datasets. Castanedo (2013) discusses fusion technologies and operational databases within business contexts. However, the functionality of fusion features and their utilities can be effectively managed through well-designed Data-Driven Systems linked to the Integrated Design Science Information System (DSIS) framework, incorporating adaptable features from Big Data.

A knowledge-based ecosystem utilizes data-cube fusion: The approach enhances understanding of various ecological systems. A data cube is generated for each ecosystem, fusing this data with information from other related ecosystems. Accurate calibrations and clearly defined rules are essential for correctly interpreting the fused data, especially in applications concerning ecosystem connectivity. Figures 4a and 4b present different 2D map views created in various geographic contexts. According to Triparty and Das (2011) and Nimmagadda and Dreher (2021c), various OLAP tools are employed to develop these fused data views, enabling interpreters to derive valuable insights.

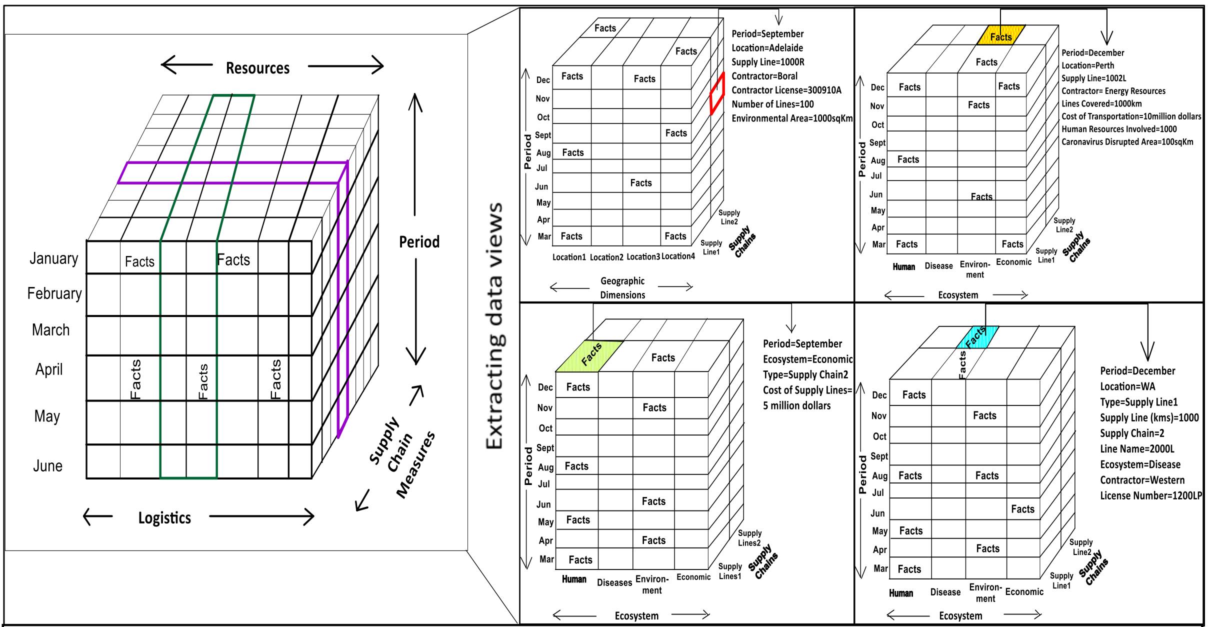

Figure 5: Fused data views, creating values in a multi-cube environment

Ecosystem data reveals intricate relationships and contexts through hierarchical data structures. The authors examine these relationships based on ecological interactions and analytical solutions, assessing their effectiveness. Key aspects include evaluating hypotheses considering ecosystems' complexities, coexistence, and connectivity. Big data systems facilitate the timely delivery of ecosystem projects, ensuring high-quality products and services even in challenging business environments. Economic conditions can become increasingly unstable due to various factors, including human, healthcare, and environmental issues that impact business ecosystems. The authors propose a systems analysis approach and resource management strategies for navigating turbulent economic times, as Nimmagadda and Dreher (2012) discussed. In line with the research objectives, the authors pose several questions about implementing metadata derived from large volumes of big data and interpreting these findings. Various plotting and mapping software solutions represent these data views, while several statistical techniques visualize and assess the value of forecasted data. The data cubes, shown in Figure 5, illustrate integrated ecological concepts within a multi-cube environment. Each cuboid structure represents different grouping elements and inherent supply chain processes, helping to explain time-series events in geographic contexts. This research encompasses 50 years of ecosystem data, generating multiple time-series components to interpret ecosystem metadata across periodic and geographic dimensions.

Forecasting Techniques – Decision Support Ecosystems: Designing digital ecosystems involves separating the information content of data and identifying factual events or features across multiple platforms. To ensure adequate provision of ecosystem services and facilitate prompt decision-making—including resource forecasting—the authors outline additional tools to examine the LSC-HHEE ecosystem community. These tools include data science, interpretive judgments, and alternative strategies for assessing supply chain costs and benefits. When making judgments and operational decisions, the influence of entrepreneurship can be integrated into the forecasting model. It is important to note that predictive tools are not designed for direct decision-making but serve as essential inputs for supply chain decision models. The research investigates data views accessed from stored metadata and produces numerical simulations that reflect various characteristics of related ecological data. The authors identify the key variables that can predict performance indicators focused on sustainability within ecosystems.

Time Series Forecasting in Ecosystem Alignments: To achieve Integrated Project Management (IPM) goals in various ecosystem contexts, the authors examine time-sequential data patterns as historical events within spatial-temporal dimensions (Hirate and Yamana, 2006). These ecosystem data patterns are analyzed to develop future forecasts, which serve as a foundation for decision-making. For this purpose, the theorization of the DSIS framework is employed alongside various statistical data mining techniques. Xu and Dobson (2019) and Comberti et al. (2015) identify trends and patterns in the data—periodic, secular, cyclical, seasonal, and irregular— which the authors in this study interpret within the LSC-HHEE ecosystem community contexts. Furthermore, forecasting functions are a guiding tool for resource management and determining ecosystem sustainability. The authors aim to identify the necessary variables for forecasting a sustainable ecosystem and the indicators of ecosystem service performance. A linear relationship exists between the demand and supply of ecosystem products and services. Additionally, an increase in logistics and supply chain expenditures can impact the service indices of ecosystems and their global management. To maintain the balance of supply and demand for ecosystem products and services, the sustainability and connectivity of embedded ecosystems are regularly monitored across periodic, secular, cyclical, seasonal, and irregular time intervals (Nimmagadda and Dreher, 2009).

Forecasting ecosystem resources through attribute modelling: The approach involves analyzing metadata perspectives to interpret valuable ecosystem products and services (Makridakis et al., 2020). In this context, we examine regression analysis, the method of least squares, and multivariate regression (Wegman and Solka, 2005). Enhancing ecosystem health and sustainability can increase the value of services by improving environmental agreements. By performing regression analysis between service value attributes and the characteristics of the HHEE ecosystem and its linked LSCE, we can evaluate the predictability of overall ecosystem sustainability. Depending on the size and complexity of the ecosystem, various regression analyses may result in straight lines or sets of curves fitted to specific data sets, which help to illustrate the relationships among variables through correlation coefficients. However, the inherent complexity of ecosystems can complicate the modelling process and analysis.

Analyzing the differences between correlation and regression in the context of ecosystems: The analysis reveals several vital attributes and insights. Correlation analysis assesses the strength of the association between measurable ecological variables. In contrast, regression analysis interprets the relationships between independent and dependent variables, often employing various types of curve fitting. The variability of attributes is significant in multiple digital ecosystem contexts (Ali and Bhaskar, 2016; Nimmagadda et al., 2021). Adhikari and Agrawal (2013) noted that exponential trends can be identified in current ecological research applications

Value-Added Interpretation of Exploratory Digital Views

The LSC and HHEE ecosystem communities contain valuable sources of ecological data. Predicting the connectivity between these systems is challenging due to the diverse products and services offered to various customers. By establishing transparent relationships and interactions between the LSC and HHEE ecosystem communities, we can better address the heterogeneity of attribute variables and the uneven conditions across these ecosystems, leading to a more practical understanding of their connectivity. Figures 6a and 6b illustrate a data reversal trend that reveals relationships and coherencies across different business periods (Nimmagadda, 2009). Quarterly data analysis identifies similar periodic trends in operating and business costs. A fiscal peak is observed in all quarters, indicating the robust functioning of the Integrated Project Management system and its business activities throughout the product and project life cycles. Polynomial equations have been fitted to the actual operating costs, along with associated fitting curves. As depicted in Figure 6b, the rounded data trends in the ecosystem are interpreted accordingly. However, the computational data suggest meaningful trends and patterns within extensive ecological datasets. The various dimensions of ecosystem data, their instances, and relevant metadata structures help us interpret these ecological data trends and patterns. For example, secular trends can indicate either increases or decreases, while cyclic trends may result from the expansion or contraction of economic resources. Seasonal deviations are analyzed for regular periodic variations, while irregular variations refer to uncontrollable fluctuations that impact business activities. Ecosystems can generate new knowledge through time-series data that reveal time-based variations.

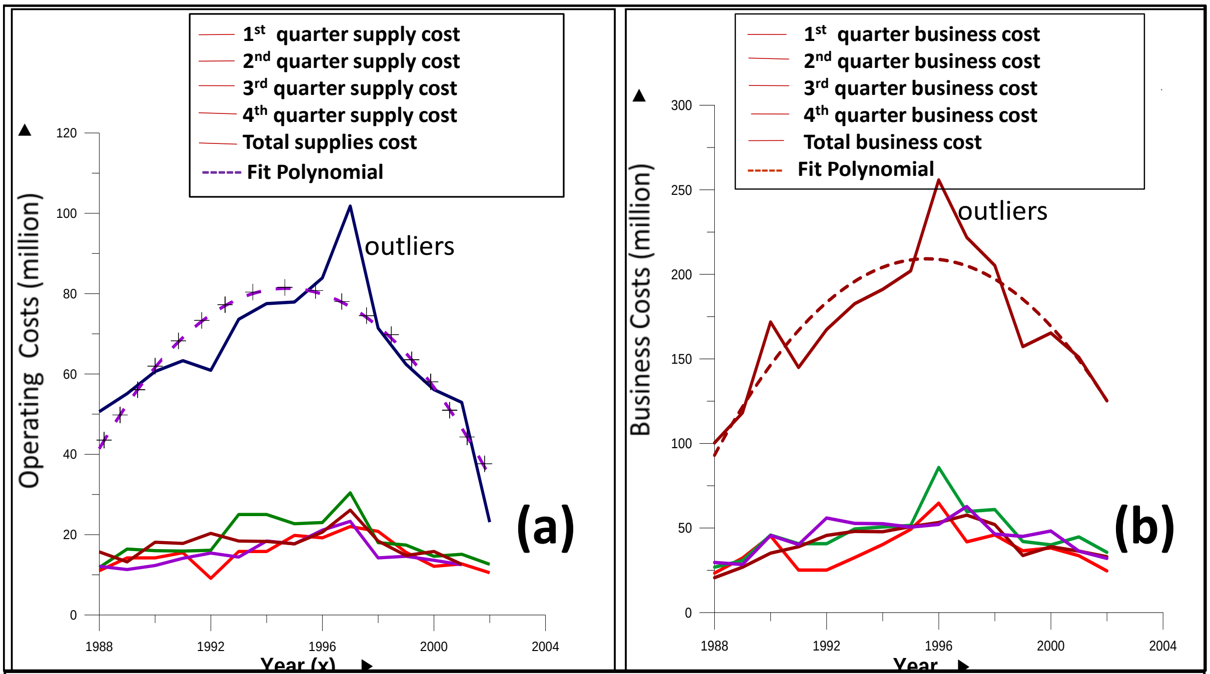

Figure 6: A business example, investigating quarterly operating and business costs extracted from ecosystem repositories (a) total supply costs; (b) total business costs

The authors utilize multidimensional linear programming and Structural Equation Modeling (SEM) to analyze the relationships within ecosystems as reflected in time-series data. This analysis uncovers both similarities and differences in patterns among individual ecosystems and across groups of ecosystems, yielding new insights from forecasting models. As noted by Nimmagadda (2015), the demand for ecosystem services and products correlates with rounding-top reversal trends, which have implications for economic development. In contrast, economic recessions can be understood through rounding-bottom reversal trends, as demonstrated in Figures 6a and 6b. Additionally, trends can be cyclic, indicating inflationary pressures. Moreover, business expansion and contraction attributes can be assessed through periodic dimensions, as conceptualized in the LSC-HHEE ecosystem construct designs and associated community metadata.

Ecosystem ontologies play a critical role in linking various ecosystems with the elements and processes of supply chains. They integrate large volumes of factual supply chain instances and calibrate them with different Information Systems (IS) constructs and models. Different data views representing the attribute dimensions of the LSC-HHEE ecosystem communities help classify the strengths of various features. For example, specific ecosystem instances documented within the human ecosystem can be connected to data view instances from healthcare (such as disease), environmental, and economic ecosystems within a comprehensive schema that stores metadata. Fine-grained data views (Rudra and Nimmagadda, 2005) effectively establish relationships between supply chain elements, processes, and their associated ecosystems, as illustrated through set theory (Gupta and Sujeet, 2014). Additionally, Figure 4 demonstrates how cuboid metadata extracts data insights from the LSC-HHEE ecosystem communities. Data and map views are plotted to visualize groups of elements or processes from multiple ecosystems with similar or different properties, enabling the visualization of high-quality products and services. Another crucial feature is the grouping of data characteristics, where multiple sets and their elements are interconnected. For example, the human element and its instances, interpreted within an ecosystem framework, connect to the LSCE community through the DSIS framework (Nimmagadda et al. 2021a). Knowledge-based data warehouse designs significantly influence data mining and the visualization of data views for interpretation. Interpreting ecosystem data requires examining deliverable research outcomes and understanding various domains and systems thoroughly, especially in integrated project contexts. Various data views, including plot and map insights, are employed to interpret the ecosystem contexts of LSCE-HHEE communities. Critical components of knowledge management include human resources, IS/IT resources, and emerging ecosystem insights. User knowledge should be commensurate with the size of individual ecosystems and their collaborative efforts in designing knowledge workflows suitable for LSC-HHEE ecosystem communities. Lastly, ecosystem metadata can be transformed into knowledge-based organizational alignments, effectively unifying digital ecosystems and enhancing the value of in-depth knowledge of repository systems and their implementation in collaborative research projects.

Ecosystem repository systems can be utilized across various dimensions and are crucial for organizing supply chains and their associated HHEE ecosystem communities. Extracting value from ecosystem metadata is essential, and it can be achieved by integrating ecosystem ontologies with linked data structures representing different geographic and demographic contexts. Obtaining reliable multidimensional data from operational sources of Integrated Project Management (IPM) is vital. The data structures implemented for each ecosystem are reusable across coexisting systems within a broad geographic and ecological community. This approach promotes the design of data warehouses on a Big Data scale, potentially reaching several terabytes of database storage. The validity of data schemas depends on evaluations specific to particular ecosystems, facilitating the creation of global schemas relevant to the LSCE-HHEE ecosystem community contexts. Nimmagadda (2015) discussed the challenges of implementing frameworks across various business contexts, identifying several challenges in integrating frameworks that manage multiple ecosystems (Moullin et al., 2020). Interpreting data views and deriving knowledge from large-scale ecosystem-bound data structures presents significant difficulties. To address these challenges, ecosystem data is organized in a denormalized format to achieve finer granularity for multidimensional data. In this research, the authors introduce ecosystem-intelligent content (EIC), which can interact with various ecological systems and manage increasing volumes of periodic data, including observable and retrievable knowledge. EIC evolves with the emergence of multiple ecosystems within a shared knowledge space. The economics of businesses depend on understanding the relationships between the LSC and HHEE ecosystems. This includes effectively conducting business operations in IPM, enhancing supply chain data management, and implementing Design Science Information Systems (DSIS) within a sustainable HHEE ecosystem community. Improved graphical solutions that reveal unknown data patterns from Big Data sources and the interconnection of multiple domains and digital ecosystem systems are vital objectives of the DSIS framework evaluations (Nimmagadda et al. 2019b). Furthermore, the DSIS can be adapted by modifying information system architectures, which may significantly impact the discovery and acquisition of new knowledge from large-scale integrated projects.

Categorizing Attribute Dimensions and Mining Rules: Kolisetty and Rajput (2021), Yao and Zhong (2000), Lampert et al. (2013), and Gornik (2003) discuss how the design of mining rules influences the categorization of attributes and their modelling. In this study, the authors propose that interpreting association rule mining within the LSC-HHEE ecosystem communities depends on identifying frequent occurrences of multidimensional attribute dimensions and their instances across various ecosystems. The classes and classification rules in ecological contexts are well-defined. For instance, similarities, differences, and scalable properties are explicitly noted for human entities and supply chain attributes across different geographic regions. Ecosystems can exhibit relational, hierarchical, and network structures that align with the mining-rule framework. Classification is essential for distinguishing the sustainability of ecosystems based on attribute instances in terms of intensity, strengths, and orientation. Furthermore, events can be mapped using 2D and 3D plots and image classifications. These tools are valuable for detailed data mining, visualization, and interpretation, offering insights into the quality of ecosystem products and services, as anticipated from integrated projects. Other methods for interpreting ecosystem-based data mining techniques include cube mining, decision tree analysis, and cluster mining.

Design of Multidimensional Ecosystem Decision Trees: Castañeda et al. (2012) and Nimmagadda et al. (2019a) developed a decision tree model designed as a classification scheme, resulting in a tree-like structure. This scheme utilizes rule mining, which includes a set of constraints for mining rules. The patterns identified represent different classes within a given dataset in a specific ecosystem. Numerical instances are interpreted using statistical and categorical data types, considering the attributes of individual LSC (Logistics and Supply Chains) and HHEE (Human-Healthcare-Economic Ecosystems) community structures. Decision tree models and data classifiers help analyze these attributes. Training and testing are conducted on datasets divided into two distinct subsets, allowing classifiers to be generated from these ecosystems. The accuracy of each classifier is subsequently evaluated. Figure 7 illustrates the decision tree mining model as a conceptual artefact, outlining various rules associated with ecosystem data instances and their trade-offs. Different HHEE ecosystems may exhibit similarities and differences in attribute representations and data instances, yet they can be classified in interpretable and meaningful ways. Researchers have employed mining rules and conceptual artefacts as decision-making tools to identify how ecosystem intelligent content (EIC) can improve the sustainability of ecological systems. The strength of the decision tree method lies in its ability to create logical model artefacts using mining rules alongside manageable numerical and categorical attribute variables. This approach provides valuable insights and significant evidence of ecosystem coexistence and connectivity within the HHEE community, supporting the use of predictive and classification models. When visualizing and interpreting ecosystems, identifying attributes of significant importance can lead to the development of sustainable, value-added ecosystem products and services. The accuracy of the ecosystem data classifier is determined by the percentage of test examples that are correctly categorized. This research has selected two distinct feature types—one derived from one ecosystem and another from a different, related ecosystem.

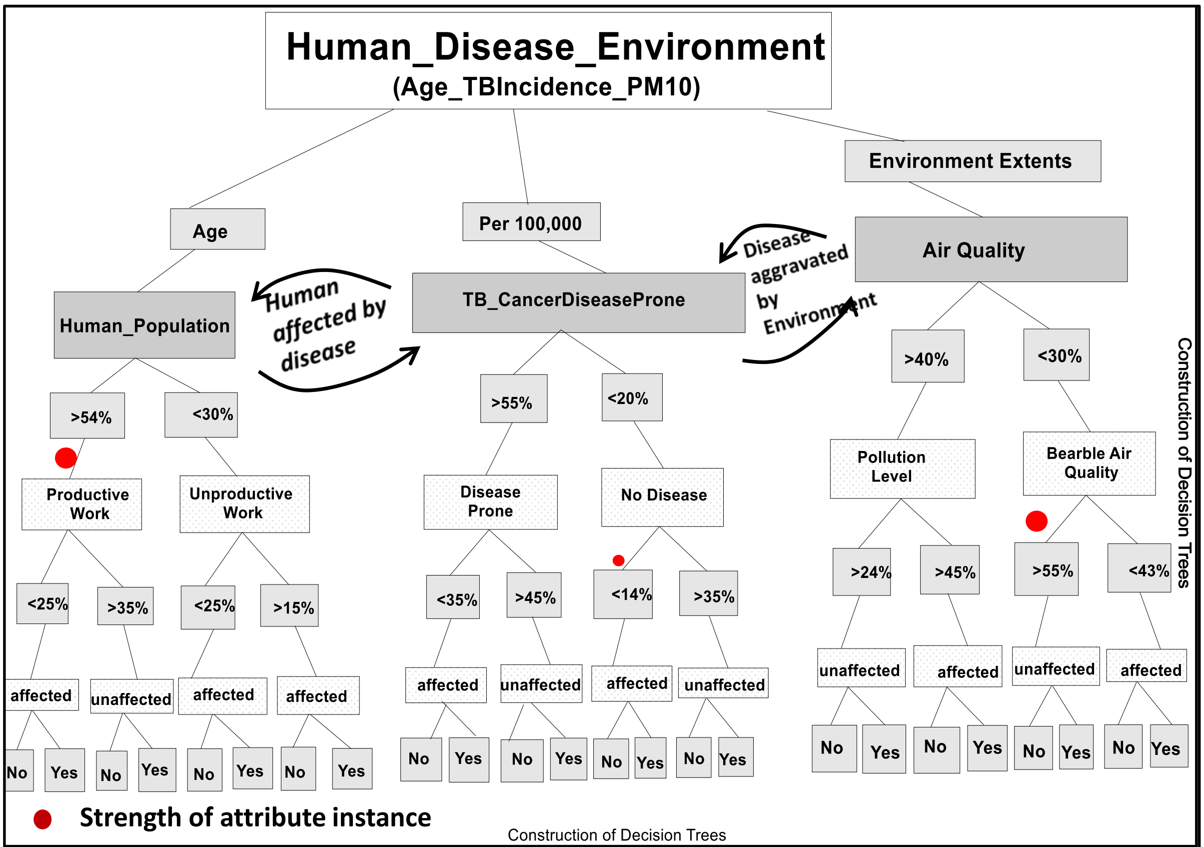

Figure 7: Multidimensional decision tree structure connecting the human, disease and environmental ecosystem events, creating values from data mining models

Ecosystem Attribute Dimension Modelling and Data Cube Analysis: Szmeja et al. (2018) highlight a dimension modelling method that uses semantically described information, primarily focusing on the hierarchical relationships between elements and processes within supply chains. Various data cube representations leverage this dimensional hierarchy to uncover new insights from multidimensional ecosystem data. Additionally, Pujari (2001) and Rudra and Nimmagadda (2005) contribute to detailed data structuring, which aids in constructing more accurate ecosystem ontologies, providing clear and interpretable insights across diverse ecosystem contexts. To effectively visualize multidimensional data views from ecosystems, it is vital to pay special attention to modelling, mining, and visualization, as Nimmagadda et al. (2021a) discussed. The structures of data cubes, often referred to as hyper-cubing, enhance the data mining process, resulting in valuable and interpretable views of ecosystem data (Djiroun and Kamel, 2018). Ecosystems encompass multiple dimensions, with each attribute dimension corresponding to sets of numerical units and measures during the modelling process. The authors emphasize that ecosystems can exhibit similarities or differences due to their multidimensional and multidirectional nature, which includes factors such as data sparsity and the density of clusters that characterize ecosystem trajectories and feature strengths (Nimmagadda et al. 2009; Nimmagadda et al. 2019b).

Embedment of Multidimensional Ecology Interpretation through Cluster Mining: In the field of ecology, patterns in ecosystem data are identified using various data mining techniques, particularly decision trees and clustering methods. These patterns are further interpreted through graphical and imaging solutions (Nimmagadda and Heinz, 2012). The multidimensional cluster analysis classifies data based on attributes such as density and sparsity. While some clusters are subtle in their visualizations, others can be significantly more illustrative depending on the strength and magnitude of the attribute instances. The authors highlight specific clusters as particularly valuable for understanding ecological connections. Existing algorithms offer partitioning and hierarchical solutions that manage multidimensional numerical and categorical data within ecosystems while maintaining the clusters' accuracy and distinguishing patterns (Duy-Tai et al., 2021). A crucial part of this modelling process involves assessing the knowledge spaces and relationship metrics between the categorized clusters. Information about the relationships between various ecosystems' attributes—mainly when many instances occur within specific groups or types of data patterns—can be instrumental in developing detailed data relationships. This is particularly relevant within the Design Science Information Systems (DSIS) knowledge management framework. Nimmagadda et al. (2021a and 2021b) illustrate that clusters are represented as bubbles of varying sizes, densities, and orientations. These variations reflect the roles of different attribute magnitudes that help to visualize diverse ecological data relationships.

Conclusions, Limitations and Future Vision

Ecosystem data are inherently geographical, often characterized as unstructured, heterogeneous, multidimensional, and sometimes scattered offline across periodic dimensions. Therefore, meticulous research is required to interpret and organize this diverse data into multidimensional repositories. While this is a significant and challenging task, it has the potential to provide insights across the complete life cycle of various domains and systems, primarily when the study encompasses diverse ecological systems and sustainable resource management in large integrated projects. Information Systems (IS) design incorporates robust constructs, models, and methods for managing ecosystem-guided repositories. This includes the mining and visualization of large volumes of ecosystem data and information. Multiple industries are engaged in these integrated projects within spatial and temporal contexts, highlighting the importance of utilizing Digital Ecosystems and Technologies (DEST) alongside Big Data technologies. There is a growing demand for DEST-guided repositories in logistically linked integrated projects, particularly those that include fusion technologies. New tools and technologies help to resolve supply chain challenges, make business decisions more geographically viable, and deliver accurate and precise information. The research emphasizes the importance of information sharing, where all entities involved with various ecosystem communities agree to protocols that facilitate this exchange. Ongoing research is focused on enhancing IS design constructs, modelling, and sustaining ecological products and services, including assessing their impacts on variable supply chains and their associated values.

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