

Supply Chain AI Education Case Library: A Multi-Dimensional Framework for Teaching Advanced Analytics in Logistics and Operations Management

Kui Meng, Jingyi Zhou, Yi Yang

School of Economics and Management, Yangtze University, Jingzhou, China

Email: guidouminzi@126.com

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Abstract

This paper proposes a conceptual multi-dimensional framework and an associated educational case library for teaching artificial intelligence in supply chain management. The framework integrates four dimensions—data authenticity, technical sophistication, business relevance, and pedagogical effectiveness—to systematically transform real-world datasets into structured learning experiences. We present three proposed educational cases: 1) Joint demand forecasting and safety stock optimization using retail inventory transaction data; 2) Multi-objective vehicle routing and fuel efficiency optimization based on logistics operations data; 3) Logistics operational risk and route performance analysis. As a conceptual framework proposal, this paper describes the design methodology, case structures, and technical specifications of the proposed educational resource. The framework is intended to serve as a scalable template for AI education in operations management, with empirical validation identified as a critical direction for future work. All cases are designed to be computationally accessible on standard laptop hardware, lowering barriers to adoption.

Keywords

Artificial Intelligence Education, Supply Chain Management, Conceptual Framework, Educational Case Library, Data-Driven Learning

1. Introduction

The integration of Artificial Intelligence into supply chain management and operations has witnessed unprecedented growth in recent years. Helo and Shamsuzzoha

(Helo & Shamsuzzoha, 2024) argued that AI represents a transformative force in supply chain and operations management, requiring systematic capability development across organizations. Major companies across retail, manufacturing, and logistics sectors have increasingly adopted AI-driven solutions for demand forecasting, inventory optimization, logistics routing, and risk management (Helo & Shamsuzzoha, 2024). However, despite this rapid technological adoption, there exists a persistent gap between AI theory and practical implementation in educational contexts.

Traditional supply chain education has predominantly focused on theoretical frameworks and simplified models that often fail to capture the complexity of real-world supply chain operations (Helo & Shamsuzzoha, 2024). Students may graduate with strong theoretical foundations but limited hands-on experience with real data and complex algorithms. This educational gap is particularly pronounced in the context of AI and machine learning applications, where the disconnect between academic theory and industrial practice is most evident (Bond et al., 2024).

The emergence of open data platforms such as Kaggle has provided unprecedented opportunities for creating authentic educational experiences. These platforms host vast repositories of real-world datasets spanning retail inventory management, logistics operations, transportation networks, and supply chain risk factors. However, the availability of data alone does not constitute effective educational resources. The challenge lies in systematically transforming these raw datasets into structured, pedagogically sound educational cases.

The demand for workforce skills in AI-powered supply chain management is growing rapidly. Employers increasingly seek graduates who can not only understand theoretical concepts but also apply advanced analytics to real business problems. This demand creates an urgent need for educational approaches that bridge the gap between classroom learning and practical application. Educational cases based on authentic data represent a promising approach to meeting this need, as they provide students with opportunities to engage with real-world complexity while developing both technical and business acumen.

1.1. Problem Statement and Research Gap

Current approaches to AI education in supply chain management face several limitations that reduce their effectiveness in preparing students for professional practice.

1.1.1. Fragmented Educational Approach

Most existing educational materials focus on isolated AI techniques or simplified supply chain scenarios. Demand forecasting is typically taught as a standalone time series problem, while inventory optimization is presented as a separate stochastic programming exercise. This fragmented approach fails to capture the interconnected nature of supply chain decisions, where forecasting accuracy directly impacts inventory policies, which in turn affect service levels and costs.

1.1.2. Lack of Real-World Data Integration

Many educational cases rely on synthetic or simplified datasets that do not reflect the complexity and scale of real-world supply chain data (Helo & Shamsuzzoha, 2024). Real supply chain data typically contains missing values, outliers, multiple data types, and complex temporal patterns. By working only with clean, simplified data, students miss the opportunity to develop crucial data preprocessing and feature engineering skills that are essential for successful AI implementation in practice.

1.1.3. Insufficient Pedagogical Framework

Existing AI educational materials often lack a systematic pedagogical framework that guides progression from basic concepts to advanced applications (Walter, 2024). Effective AI education requires a structured approach that builds skills incrementally, starting with foundational concepts and progressively introducing more complex techniques and broader problem contexts (Celik, 2024). The absence of such scaffolding in existing resources limits their educational effectiveness.

1.2. Research Objectives

This research proposes a conceptual framework and case library design to address these gaps. Our primary objectives are:

- 1) To propose a multi-dimensional educational framework that integrates data authenticity, technical sophistication, business relevance, and pedagogical effectiveness for AI education in supply chain management.
- 2) To describe three educational cases that demonstrate the application of AI techniques to supply chain problems, including joint demand forecasting and safety stock optimization, multi-objective vehicle routing, and logistics operational risk analysis.
- 3) To establish an open-source, reproducible educational resource design that can be adopted and adapted by educators worldwide.

This paper presents a conceptual design. Empirical validation through classroom implementation and learning outcome assessment is identified as essential future work.

2. Literature Review

2.1. AI Education in Higher Education

The integration of AI into higher education has evolved significantly over the past decade. Early approaches focused primarily on theoretical foundations, algorithmic understanding, and mathematical formalism (Russell & Norvig, 2020). However, as AI technologies have become more accessible and applicable across diverse domains, educators have recognized the need for more practical, application-oriented AI education.

Research on AI literacy has identified key competencies that students need to

develop for effective engagement with AI technologies. Touretzky et al. (Touretzky et al., 2019) established foundational guidelines for AI education, proposing five core ideas that every student should understand about AI. Walter (Walter, 2024) extended this work by proposing a comprehensive framework for AI literacy, competency, and readiness in educational contexts, emphasizing the importance of preparing students for an AI-driven future while addressing both technical skills and ethical considerations. Celik (Celik, 2024) conducted a scoping review of AI literacy in teacher education and identified critical components including AI knowledge, pedagogical integration strategies, and ethical awareness.

Bond et al. (Bond et al., 2024) conducted a comprehensive meta systematic review of research on AI applications in higher education, analyzing a wide range of publications. They found that while AI is increasingly used in higher education for profiling, prediction, assessment, and adaptive systems, there is a notable scarcity of research on pedagogical approaches for teaching AI itself. They called for more research on how to effectively integrate AI education into domain-specific curricula and emphasized the need for increased ethical rigor in AI education research.

Wang and Cheng (Wang & Cheng, 2025) further examined the societal impacts of AI tools, particularly their effects on cognitive offloading and critical thinking skills. Their research highlighted concerns that over-reliance on AI without adequate educational frameworks could diminish essential analytical capabilities, underscoring the importance of pedagogical approaches that balance AI tool use with the development of independent reasoning skills.

Molenaar et al. (Molenaar et al., 2024) examined the promises and challenges of generative AI for human learning, highlighting both the transformative potential of these technologies and the critical need for evidence-based pedagogical frameworks to guide their integration in educational settings. Luckin et al. (Luckin et al., 2016) further argued that AI has the potential to transform education through personalized learning, but emphasized the need for robust pedagogical frameworks to guide AI integration. Their work emphasized that effective AI education must move beyond technological proficiency to develop deeper understanding of AI capabilities and limitations.

The emergence of open educational resources and massive open online courses has begun to address some accessibility challenges. However, these resources often lack the depth and structure needed for comprehensive domain-specific AI education (Adiguzel et al., 2024). Most existing resources focus on generic AI concepts, leaving educators in specialized fields such as supply chain management to develop their own teaching materials. Joseph and Lee (Joseph & Lee, 2025) conducted a global study of higher education students' perceptions of ChatGPT, finding significant variation across academic programs, geographic regions, and demographic factors. Their research highlighted the need for tailored AI education approaches that address the specific needs and concerns of different student populations.

2.2. Supply Chain and Operations Management Education

Supply chain and operations management education has traditionally emphasized analytical models, optimization techniques, and theoretical frameworks. Classic textbooks have focused on inventory theory, facility location, production planning, logistics optimization, and quality management (Christopher, 2016).

The evolution of SCOM education reflects broader changes in the business environment. Early curricula emphasized mathematical modeling and deterministic optimization. As computing power increased, stochastic models and simulation became more prominent. More recently, the emergence of big data and AI has created demand for data-driven decision-making skills that go beyond traditional analytical methods.

Helo and Shamsuzzoha (Helo & Shamsuzzoha, 2024) proposed a comprehensive capability-based framework for understanding generative AI in supply chain and operations management. Their framework identifies key capability areas including AI-driven demand forecasting, intelligent inventory management, autonomous logistics operations, and adaptive risk assessment. They argued that these capabilities fundamentally reshape the skills and knowledge required for supply chain professionals, creating an urgent need for updated educational approaches.

Lee and Park (Lee & Park, 2025) conducted a systematic review of prompt engineering in higher education, identifying key competencies that students need to develop for effective human-AI interaction and highlighting the implications for curriculum design across disciplines including supply chain management.

The gap between traditional SCOM education and industry needs has been increasingly recognized. Shaik et al. (Shaik et al., 2024) conducted a comprehensive literature review on the integration of AI in educational contexts and identified critical success factors including curriculum alignment, teacher readiness, and institutional support. Kamalov et al. (Kamalov et al., 2024) further emphasized that higher education institutions must adapt their curricula to prepare students for an AI-augmented workplace, with particular attention to domain-specific applications.

Graduates entering supply chain roles are expected to be proficient with data analytics tools, understand machine learning concepts, and be able to apply these techniques to real business problems. Meeting these expectations requires educational approaches that combine analytical rigor with practical application.

2.3. Case-Based Learning in Operations Management

Case-based learning has long been recognized as an effective pedagogical approach in business education. Since the Harvard Business School pioneered the case method in the early twentieth century, cases have become a cornerstone of management education (Eisenhardt, 1989).

Cases provide rich, contextualized learning experiences that help students develop critical thinking, problem-solving, and decision-making skills. By engaging with real or realistic business scenarios, students learn to analyze complex situa-

tions, identify key issues, and develop actionable recommendations (Yin, 2018). The case method is particularly effective for developing the judgment and analytical skills that are essential for managerial decision-making.

In operations management, cases have traditionally focused on strategic and tactical decision-making scenarios based on real companies and industries (Eisenhardt, 1989). Classic OM cases address facility location decisions, production planning, inventory management, and logistics network design. However, these cases have typically been qualitative or semi-quantitative, with limited emphasis on data analytics and computational methods.

Ahmad et al. (Ahmad et al., 2025) conducted a comprehensive systematic review of AI in education, identifying key trends, benefits, and challenges across implementation contexts. Their work demonstrated that technology-enhanced learning environments can significantly improve educational outcomes when properly designed, while emphasizing the critical importance of pedagogical design principles including authentic problem-solving, scaffolded learning experiences, and continuous assessment. Shaik et al. (Shaik et al., 2024) further emphasized that effective AI integration in education requires careful attention to curriculum alignment and institutional support.

Rudolph and Tan (Rudolph & Tan, 2025) examined the barriers to digital transformation in higher education institutions, identifying critical success factors including faculty readiness, infrastructure investment, and strategic leadership. Their research showed that personalized, data-driven learning experiences can be effectively implemented across diverse educational contexts through careful curriculum design and appropriate technological infrastructure.

The integration of data analytics and AI into case-based learning represents a significant evolution in this pedagogical approach. Data-rich cases combine narrative-driven scenarios with hands-on data analysis and model building activities. These cases provide students with authentic learning experiences that bridge theory and practice, while developing both technical and business skills.

2.4. Existing Educational Technology Frameworks

Several established frameworks inform the design of technology-enhanced education. The Technological Pedagogical Content Knowledge (TPACK) framework emphasizes the interrelationship between technology, pedagogy, and content knowledge. The Substitution, Augmentation, Modification, and Redefinition (SAMR) model describes progressive levels of technology integration. The Analysis, Design, Development, Implementation, and Evaluation (ADDIE) model provides a systematic approach to instructional design.

While these frameworks provide valuable guidance for educational technology integration, they are designed for general educational contexts and do not specifically address the unique challenges of AI education in domain-specific fields such as supply chain management. Rudolph and Tan (Rudolph & Tan, 2025) identified critical barriers to digital transformation in higher education, emphasizing the

need for context specific frameworks that address the unique challenges of different disciplines. Sullivan and Kelly (Sullivan & Kelly, 2026) proposed six institutional intervention areas to support ethical and effective student use of generative AI, developing a comprehensive approach that addresses academic integrity while leveraging AI's educational potential. The framework proposed in this paper builds upon these foundations while focusing specifically on the integration of data, technology, business relevance, and pedagogical design for AI education in supply chain contexts.

2.5. Synthesis and Research Gap

The literature review reveals several important findings. First, there is growing demand for AI education in supply chain management driven by industry needs. Second, existing educational resources tend to be fragmented, lacking integration across AI techniques and supply chain domains. Third, established pedagogical approaches such as case-based learning provide a solid foundation but need to be extended to incorporate data-driven, computational components.

The proposed framework addresses these gaps by providing a systematic approach for designing AI education cases in supply chain management. The four dimensions—data, technology, business, and education—provide a comprehensive structure for case development that ensures authenticity, rigor, relevance, and pedagogical effectiveness.

3. Proposed Framework

3.1. Multi-Dimensional Educational Framework

We propose a four-dimensional conceptual framework for AI education in supply chain management (Figure 1). Each dimension addresses a critical aspect of effective AI education and together they provide a comprehensive structure for case design and development.

The four dimensions—data authenticity, technical sophistication, business relevance, and pedagogical effectiveness—were derived through a systematic analysis of the literature and practice needs identified in Section 2. First, the repeated emphasis on real-world data integration across AI education studies (Helo & Shamsuzzoha, 2024; Bond et al., 2024; Shaik et al., 2024) and the capability requirements identified by Helo and Shamsuzzoha (Helo & Shamsuzzoha, 2024) for AI-driven supply chain operations informed the data and technology dimensions. Second, the business dimension was motivated by the industry demand for graduates who can bridge theory and practice, as highlighted by multiple studies on supply chain management education (Christopher, 2016; Kamalov et al., 2024). Third, the pedagogical effectiveness dimension was grounded in established learning theories including TPACK, SAMR, and ADDIE models (Section 2.4), as well as the scaffolding principles identified by Walter (Walter, 2024) and Celik (Celik, 2024) for AI literacy development. The three cases were then designed to cover the core supply chain operational domains identified in the literature: inventory manage-

ment (upstream), logistics routing (midstream), and operational risk assessment (downstream), each progressively increasing in technical complexity to align with pedagogical scaffolding principles (Eisenhardt, 1989; Yin, 2018).

Multi-Dimensional Framework for AI Education in Supply Chain Management

Integration of Data, Technology, Business, and Education Dimensions

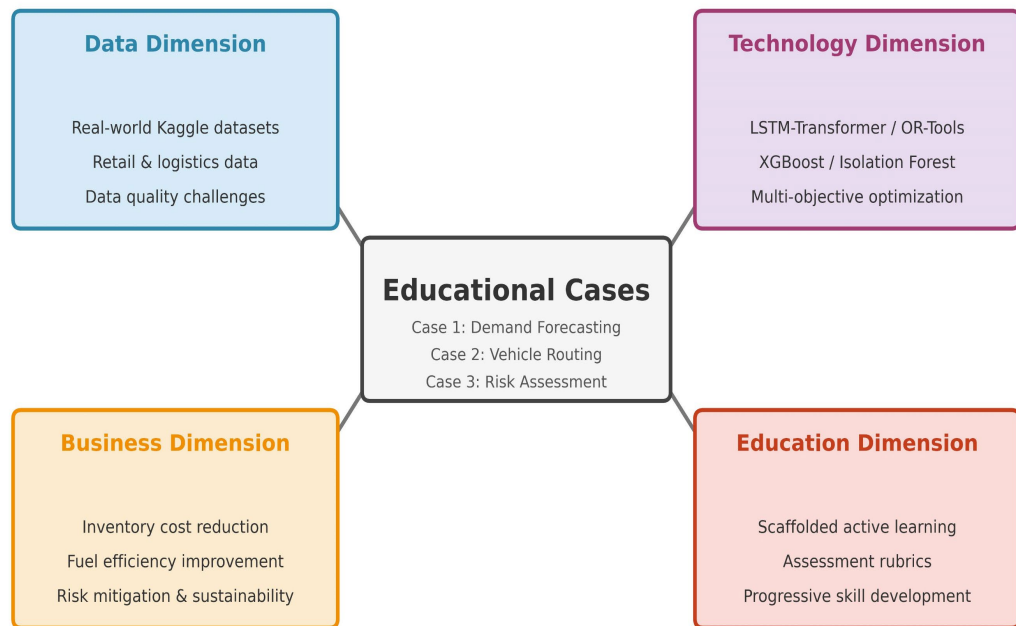


Figure 1. Multi-dimensional framework architecture showing the integration of data, technology, business, and education dimensions. The four dimensions work together to transform authentic datasets into structured educational experiences.

3.1.1. Data Dimension

The data dimension emphasizes the use of authentic, real-world datasets that reflect the complexity, scale, and characteristics of actual supply chain operations. Real data contains noise, missing values, outliers, and complex structures that challenge students to develop robust data preprocessing and analysis skills. The proposed framework leverages publicly available Kaggle datasets spanning multiple supply chain domains, including retail inventory management, logistics operations, and transportation risk factors.

Key considerations for the data dimension include: data quality and completeness, data size and complexity, relevance to supply chain operations, documentation and metadata quality, and licensing and ethical considerations.

Observable criteria for data authenticity: 1) Dataset contains at least 1000 records with multiple variables relevant to the supply chain domain; 2) Data exhibits realistic imperfections such as 5% - 15% missing values, outliers, and noise; 3) Data includes temporal or spatial structure reflecting real operational patterns; 4) Dataset documentation provides clear variable definitions and collection methodology; 5) Data is publicly available under permissive licenses enabling educational

use. Educators can use these criteria to evaluate whether a dataset meets the threshold for authentic learning experiences.

3.1.2. Technology Dimension

The technology dimension focuses on the application of AI and machine learning techniques to supply chain problems. The proposed framework incorporates a range of AI methodologies at varying levels of complexity, enabling progressive skill development. These include deep learning for demand forecasting, multi-objective optimization for logistics routing, ensemble methods for risk prediction, and anomaly detection for performance evaluation.

Key considerations for the technology dimension include: appropriate technique selection for each problem, implementation complexity suitable for educational contexts, availability of open-source tools and libraries, computational requirements, and opportunities for experimentation and exploration.

Observable criteria for technical sophistication: 1) Techniques can be implemented using open-source libraries (e.g., TensorFlow, scikit-learn, OR-Tools) without proprietary software; 2) Model training completes within 30 minutes on standard laptop hardware (16 GB RAM, CPU-based); 3) Code complexity remains below 500 lines per component, enabling student comprehension; 4) Methods allow for parameter experimentation so students can observe sensitivity effects; 5) Results are reproducible with fixed random seeds and documented version dependencies. These criteria ensure that technical components are educationally tractable rather than research-grade implementations.

3.1.3. Business Dimension

The business dimension grounds each case in real business scenarios and addresses concrete business challenges. This dimension ensures that students understand not only how to apply AI techniques but also why these techniques matter for business performance. Cases address challenges such as inventory cost reduction, fuel efficiency improvement, risk mitigation, and driver performance evaluation.

Key considerations for the business dimension include: relevance to current industry practice, clear business value proposition, appropriate problem scope, consideration of multiple stakeholder perspectives, and integration of sustainability and ethical considerations.

Observable criteria for business relevance: 1) The case addresses a problem cited in recent industry reports or academic supply chain literature; 2) Quantifiable business metrics can be calculated from student solutions (e.g., inventory cost reduction percentage, fuel efficiency improvement, risk score accuracy); 3) The problem involves at least two stakeholder perspectives (e.g., cost vs. service level, efficiency vs. sustainability); 4) Case outcomes can be benchmarked against industry standards or published case studies; 5) Students can articulate the business value of their AI solution in non-technical terms. These criteria ensure that students develop both analytical capabilities and business acumen.

3.1.4. Education Dimension

The education dimension focuses on pedagogical design and learning outcomes. The proposed framework incorporates established educational principles including scaffolding, active learning, authentic assessment, and progressive complexity. Each case is designed to achieve specific learning objectives that build upon each other across the case library.

Key considerations for the education dimension include: alignment with learning objectives, appropriate difficulty progression, engagement and motivation factors, assessment methods and rubrics, and flexibility for different educational contexts.

Observable criteria for pedagogical effectiveness: 1) Each case specifies 3 - 5 measurable learning objectives using Bloom's taxonomy action verbs (e.g., analyze, implement, evaluate); 2) Assessment rubrics define three performance levels (developing, proficient, advanced) with concrete evidence requirements; 3) Case completion time is calibrated to 8 - 12 hours for a student at the target level, allowing integration into a standard course module; 4) Pre-case and post-case knowledge checks can be administered to measure learning gains; 5) Instructor materials include discussion questions that connect technical results to business decisions. These criteria enable educators to consistently evaluate and adapt cases for their specific instructional contexts.

3.2. Dimension Interactions

The four dimensions are not independent but interact synergistically. The data dimension provides the raw material for technical analysis, which is framed by business context and structured by pedagogical design. Technical analysis of real data generates insights that have business value, while pedagogical design ensures that these insights are accessible and meaningful for learners.

For example, in the demand forecasting case, the data dimension provides authentic inventory transaction data. The technology dimension enables deep learning-based forecasting. The business dimension frames this as a concrete challenge of balancing inventory costs and service levels. The education dimension structures the learning experience through progressive exercises and assessment activities.

3.3. Case Design Principles

The proposed case development methodology follows a systematic iterative process guided by the following principles.

3.3.1. Authenticity

Cases should be based on real data and realistic business scenarios. Authenticity enhances student engagement and ensures that skills developed are transferable to professional practice.

3.3.2. Progressive Complexity

Cases should be designed to build skills incrementally, with each case introducing

new concepts and techniques while reinforcing previously learned material. The three proposed cases follow a progression from foundational to advanced.

3.3.3. Reproducibility

All materials should be openly available with complete documentation, enabling educators worldwide to adopt and adapt the cases for their specific contexts. This includes source code, datasets, and detailed instructions.

3.3.4. Flexibility

Cases should be adaptable to different educational contexts, including varying course lengths, student backgrounds, and learning objectives. Multiple entry points and pathways enable customization.

3.3.5. Ethical Considerations

All datasets proposed for use in these cases are publicly available and comply with Kaggle's terms of use. The cases are designed under open-source principles to ensure reproducibility. Ethical discussions on fairness, transparency, and explainability in AI applications are integrated into each case as part of the learning objectives.

4. Proposed Case Library

4.1. Overview

The proposed case library consists of three educational cases spanning different supply chain domains and progressively increasing in technical complexity. **Figure 2** provides an overview of the three cases and their interconnections.

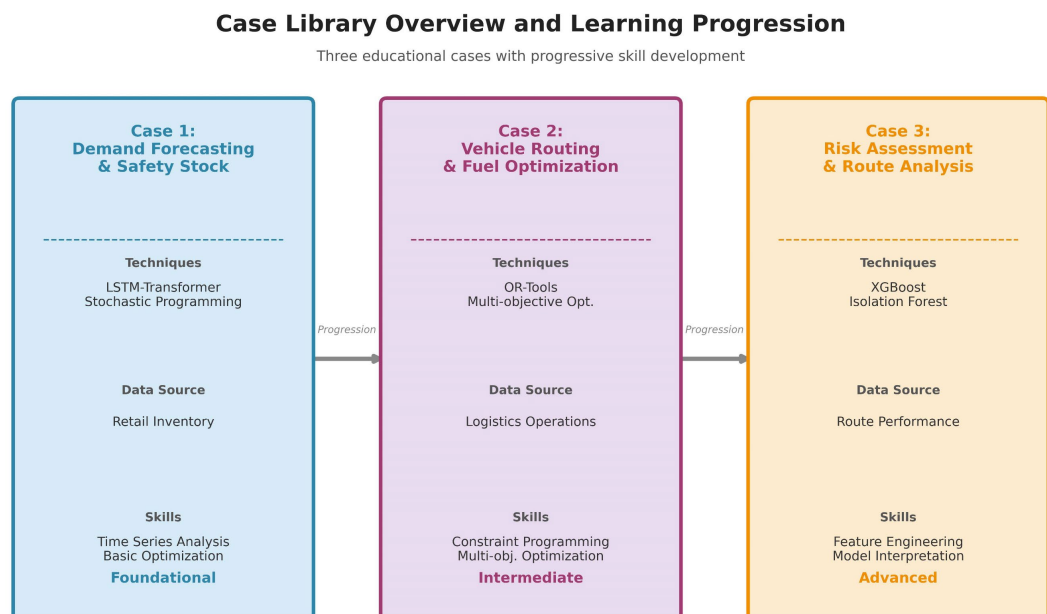


Figure 2. Overview of three educational cases showing progressive skill development from foundational to advanced. Each case builds upon skills developed in previous cases while introducing new techniques and broader problem contexts.

Target Learner Level and Implementation Context: The proposed case library is designed for upper-level undergraduate or graduate students in supply chain management, operations research, or business analytics programs. Prerequisites include introductory statistics, basic Python programming (variables, functions, pandas dataframes), and familiarity with supply chain concepts (inventory policies, routing problems, service level metrics). No prior machine learning experience is assumed; the cases are structured to introduce AI techniques progressively. Each case is designed as a 2-week module (8 - 12 hours of student effort), suitable for integration into a 15-week semester course on supply chain analytics or as a standalone intensive workshop. Student learning would be assessed through: 1) Code submission implementing the required models with correct methodology (30%); 2) Written analysis interpreting model outputs and connecting technical results to business recommendations (35%); 3) Parameter experimentation report demonstrating understanding of model sensitivity (20%); 4) Peer discussion or presentation defending their solution approach (15%). All assessment rubrics are designed with three performance levels: developing (basic implementation with guidance), proficient (correct independent completion), and advanced (creative extension beyond requirements).

4.2. Case 1: Joint Demand Forecasting and Safety Stock Optimization

4.2.1. Data Source

Case 1 is based on the “Inventory Optimization for Retail” dataset from Kaggle, containing inventory transaction data for retail operations. The dataset includes approximately 18,000 transaction records across 20 product categories, spanning 6 months of daily sales data (January-June 2020). Each record contains variables for product category, sales quantity, unit price, promotional status, inventory level, and transaction date. A proposed train/validation/test split of 70/15/15 is recommended, with training data covering the first 4 months, validation data covering month 5, and test data covering the final month. The dataset provides rich opportunities for demand forecasting and inventory optimization analysis, with approximately 500 KB of structured data.

The dataset is publicly available at:

<https://www.kaggle.com/datasets/suvroo/inventory-optimization-for-retail>.

This dataset was chosen because it contains the core variables required for teaching demand forecasting and inventory optimization: temporal sales records (date, quantity), product attributes (category, price, promotion status), and inventory levels. These variables enable students to practice both predictive modeling (forecasting future demand) and prescriptive analytics (optimizing safety stock based on forecast uncertainty). However, educators should note several teaching limitations: the dataset contains approximately 18,000 transaction records across 20 product categories over a limited time period, which may not capture full seasonal cycles or long-term trends. Additionally, the retail context is simplified to a single store location, omitting multi-echelon inventory challenges. These limita-

tions are pedagogically intentional—they reduce complexity for introductory learning while still requiring students to handle missing values, outliers, and categorical encoding. Instructors seeking greater complexity can extend the case by supplementing the dataset with external weather or economic data.

4.2.2. Business Problem

The case addresses the fundamental challenge of balancing inventory costs with service levels in retail operations. Retail organizations must maintain sufficient inventory to meet customer demand while minimizing holding costs and avoiding overstock. Traditional approaches treat demand forecasting and safety stock determination as separate processes, often leading to suboptimal inventory policies.

This case demonstrates how these processes can be integrated through joint optimization. By combining deep learning-based demand forecasting with stochastic inventory optimization, students learn to develop inventory policies that achieve target service levels while minimizing total inventory costs. The integrated approach captures the interdependence between forecast accuracy and inventory performance.

4.2.3. Technical Specifications

The following technical specifications describe a proposed educational design for the demand forecasting component. The hybrid LSTM-Transformer architecture was selected because it illustrates key deep learning concepts (sequential modeling, attention mechanisms) while remaining implementable within a single course module. All hyperparameters listed below are illustrative defaults intended to provide students with a functional starting point; they are not validated as optimal baselines. Educators are encouraged to treat these as pedagogical scaffolding that students can modify and experiment with to understand parameter sensitivity.

Proposed Deep Learning Model Architecture:

- Input Features: 15 features including temporal features (day of week, month, seasonality), product features (category, price, promotion flags), and store features (location, size, historical performance)
- LSTM Layers: 2 layers with 128 and 64 hidden units respectively
- Transformer Layers: 2 encoder layers with 4 attention heads and 256-dimensional embeddings
- Dropout Rate: 0.2 for regularization
- Activation Function: ReLU for hidden layers, linear for output layer
- Loss Function: Huber loss combined with MAPE for robust training

Model Hyperparameters:

- Learning Rate: 0.001 (Adam optimizer)
- Batch Size: 32 sequences
- Sequence Length: 30 days input, 7 days prediction horizon
- Training Epochs: 100 with early stopping (patience = 15)
- Validation Split: 20% of training data
- Regularization: L2 weight decay of $1e-4$

Safety Stock Optimization:

The safety stock component is designed to use stochastic programming as follows:

- Service Level Target: 95% (configurable parameter)
- Holding Cost Rate: 25% of item value per year
- Stockout Cost: 2x holding cost (reflecting lost sales impact)
- Demand Uncertainty: Monte Carlo simulation with 1000 iterations
- Lead Time Distribution: Empirical distribution derived from historical data
- Optimization Algorithm: Stochastic gradient descent with constraint handling

Implementation Environment:

The hyperparameters and model configurations listed above (including 100 training epochs, 1000 Monte Carlo iterations, learning rate 0.001, and specific layer dimensions) are proposed as pedagogically motivated starting values. They are not derived from empirical experiments conducted in this study, and no training results or performance metrics are reported because this paper presents a conceptual design rather than an implementation report. Educators adopting these cases should treat all numerical settings as initial defaults that students are expected to modify during the learning process. The values were selected based on common practices in educational machine learning literature to ensure models converge within reasonable timeframes on standard hardware while providing sufficient complexity to illustrate key concepts.

- Python Version: 3.11
- TensorFlow Version: 2.15.0
- Pandas Version: 2.2.0
- NumPy Version: 1.26.4
- Scikit-learn Version: 1.4.2
- Hardware: Standard laptop with 16 GB RAM, no GPU required

4.2.4. Learning Objectives

Technical Objectives:

- Understand principles and implementation of deep learning for time series forecasting
- Learn to quantify and incorporate forecast uncertainty into inventory decisions
- Develop skills in stochastic optimization and inventory policy design

Business Objectives:

- Gain experience with TensorFlow and modern deep learning frameworks
- Understand trade-offs between inventory costs and service levels
- Learn how integrated approaches can improve supply chain performance
- Develop appreciation for practical challenges in retail inventory management

4.3. Case 2: Multi-Objective Vehicle Routing and Fuel Efficiency Optimization

4.3.1. Data Source

Case 2 is based on the “Delhivery Dataset” from Kaggle (approximately 9.1 MB),

containing real-world logistics operations data from a major Indian logistics company. The dataset includes approximately 150,000 shipment records across 20+ service regions in India, collected over a 12-month period (2021-2022). Each record contains variables for route origin and destination, trip distance (km), planned and actual delivery times, vehicle type and capacity, fuel consumption (liters), and geographic coordinates. A proposed train/validation/test split of 70/15/15 is recommended based on temporal ordering (chronological split) to simulate real-world deployment where models predict future routes based on historical patterns. The dataset represents a comprehensive view of logistics operations, providing rich opportunities for route optimization and operational analysis.

The dataset is publicly available at:

<https://www.kaggle.com/datasets/santanukundu/delhivery-dataset>.

The Delhivery dataset was selected because it provides comprehensive logistics operational variables essential for teaching multi-objective optimization: shipment route distances, delivery timestamps (actual vs. planned), vehicle type and capacity, fuel consumption metrics, and geographic coordinates across multiple Indian cities. These variables enable students to model real-world trade-offs between delivery efficiency, fuel consumption, and service quality that mirror the complexities identified in contemporary logistics education research (Helo, 2024; Kamalov et al., 2024). Teaching limitations include: the dataset reflects Indian logistics infrastructure and may not generalize to all geographic contexts; some fuel consumption values are estimated rather than measured; and the data lacks detailed driver-level attributes that would enable workforce analytics. Educators should discuss these limitations with students as part of the learning experience, emphasizing how dataset characteristics influence model validity and the importance of understanding data provenance before analysis.

4.3.2. Business Problem

The case addresses the complex challenge of optimizing vehicle routing decisions while balancing multiple objectives. Logistics companies must consider delivery time, fuel consumption, driver satisfaction, equipment utilization, and environmental impact when planning routes. Traditional vehicle routing problems typically focus on single objectives such as minimizing total distance.

This case demonstrates multi-objective optimization that balances competing objectives. Students learn to configure and evaluate different objective weight combinations, understand trade-offs between operational efficiency and sustainability, and develop practical routing solutions that consider multiple stakeholder perspectives.

4.3.3. Technical Specifications

The technical specifications below describe a proposed educational design using Google OR-Tools, which was chosen because it provides an accessible, well-documented platform for teaching combinatorial optimization without requiring stu-

dents to implement algorithms from scratch. This approach aligns with pedagogical recommendations for scaffolded learning (Celik, 2024), allowing students to focus on problem formulation and trade-off analysis rather than low-level implementation. All solver parameters (time limits, default weights, strategy selections) are illustrative defaults that enable functional solutions; instructors should encourage students to experiment with alternative configurations to understand how parameter choices affect solution quality and computation time.

1) OR-Tools Configuration

The optimization uses Google OR-Tools:

- Solver Type: Routing Solver with Guided Local Search
- Time Limit: 300 seconds per instance
- First Solution Strategy: PATH_CHEAPEST_ARC
- Number of Vehicles: Configurable (default: 10)
- Capacity Constraints: From dataset
- Time Windows: Hard constraints from customer requirements

Multi-objective Formulation:

$$\text{Minimize } Z = w_1 \cdot D + w_2 \cdot F + w_3 \cdot V \quad (1)$$

where D is total distance, F is fuel consumption, and V is driver workload variance. Default weights: $w_1 = 0.4$, $w_2 = 0.4$, $w_3 = 0.2$, configurable by students.

2) Fuel Consumption Model

- Base Rate: 8.5 L/100 km (empty truck)
- Load Factor: +0.3 L/100 kg cargo
- Speed Range: Optimal 60 - 80 km/h
- Terrain Factor: Derived from route elevation data

3) Environmental Impact

Carbon emissions calculation follows standard conversion:

- Diesel CO₂ Factor: 2.68 kg CO per liter
- Emission Reduction Target: 30% reduction from baseline

4) Implementation Environment

Same as Case 1 (Python 3.11, TensorFlow 2.15.0). Additional dependency: Google OR-Tools 9.8.

4.3.4. Learning Objectives

1) Technical Objectives

- Understand principles of multi-objective optimization
- Learn to model and solve vehicle routing problems with multiple constraints
- Develop skills in constraint programming and combinatorial optimization
- Gain experience with OR-Tools

2) Business Objectives

- Understand trade-offs between logistics objectives and stakeholder interests
- Learn to integrate sustainability into operational decision-making
- Develop appreciation for complexity of logistics operations

4.4. Case 3: Logistics Operational Risk and Route Performance Analysis

4.4.1. Data Source

Case 3 uses operational performance data from the Delhivery logistics dataset, containing detailed records of shipment routes, trip distances, delivery times, fuel consumption, and regional operational metrics. The data enables analysis of route efficiency patterns, delivery performance variability, and operational risk indicators across multiple service regions.

4.4.2. Business Problem

The case addresses operational risk assessment in logistics networks. Logistics companies face challenges including delivery delays, route inefficiencies, and variable fuel consumption that impact both service quality and operational costs. Traditional performance evaluation relies on single metrics such as average delivery time or total distance. This case demonstrates how machine learning can identify multidimensional risk factors and predict operational outcomes based on route characteristics and historical performance data.

4.4.3. Technical Specifications

The specifications below describe a proposed educational design using XGBoost, selected because it represents a state-of-the-art ensemble method that illustrates key machine learning concepts (boosting, regularization, feature importance) while remaining computationally efficient for classroom use. XGBoost was chosen over deep learning alternatives for this advanced case because its built-in feature importance metrics support model interpretability—a critical learning objective for risk analysis. The hyperparameters listed (learning rate, max depth, subsampling ratios, regularization constants) are illustrative defaults that produce functional models; they serve as pedagogical starting points rather than optimized baselines. Students should be encouraged to modify these parameters and observe effects on model performance and generalization, thereby developing intuitive understanding of the bias-variance trade-off.

1) XGBoost Model Configuration

- Learning Rate: 0.1
- Maximum Depth: 6
- Number of Estimators: 100
- Subsample: 0.8
- Column Subsample: 0.8
- Regularization: $\alpha = 1$, $\lambda = 1$
- Objective: binary: logistic (delay classification) or regression (duration prediction)
- Metric: AUC for classification; RMSE for regression

2) Feature Engineering

Operational risk indicators derived from the data include:

- Route Distance: Total trip distance categorized into short, medium, and long

hauls

- Duration Variability: Standard deviation of delivery times for similar route types
- Fuel Efficiency Ratio: Actual vs. expected fuel consumption based on distance
- Regional Performance: Average delivery time deviation by service region
- Temporal Patterns: Performance variation by day of week, month, and season
- Load Factor Impact: Relationship between shipment characteristics and delivery
- outcomes

3) Operational Risk Score

$$Risk\ Score = 0.3 \cdot D_{norm} + 0.3 \cdot T_{var} + 0.2 \cdot F_{eff} + 0.2 \cdot R_{perf} \quad (2)$$

where D_{norm} is normalized route distance, T_{var} is delivery time variability, F_{eff} is fuel efficiency deviation, and R_{perf} is regional performance index. Weights reflect the relative contribution of each factor to operational risk, with distance and time variability weighted higher due to their direct impact on customer service levels. High-risk routes are classified as those with scores above the median.

4) Clustering Analysis

K-means clustering is applied to identify natural groupings of routes based on performance characteristics:

- Number of Clusters: 3 - 5 (determined by elbow method)
- Features: Distance, duration, fuel consumption, regional indicators
- Interpretation: Each cluster represents a distinct operational profile (e.g., high-efficiency short hauls, long-distance variable routes, regional standard operations)

5) Implementation Environment

Same as Case 1 (Python 3.11, TensorFlow 2.15.0). Additional dependencies: XGBoost 2.0.3, Scikit-learn 1.4.2.

4.4.4. Learning Objectives

1) Technical Objectives:

- Understand ensemble methods for classification and regression
- Learn feature engineering for operational risk prediction
- Develop clustering and pattern recognition skills
- Gain experience with XGBoost and unsupervised learning

2) Business Objectives:

- Understand multidimensional nature of logistics operational risk
- Learn how data-driven approaches improve route planning and resource allocation
- Develop appreciation for trade-offs between service speed, cost, and reliability

4.5. Integrated Case Library Design

The three cases form a progressive learning sequence:

- Case 1 (Foundational): Data preprocessing, time series analysis, basic optimization
- Case 2 (Intermediate): Data integration, constraint programming, multi-objective optimization
- Case 3 (Advanced): Machine learning, feature engineering, model interpretation

The cases also cover complementary supply chain domains: Case 1 addresses upstream inventory management, Case 2 focuses on midstream logistics, and Case 3 addresses downstream operational risk management. This structure provides students with a comprehensive view of AI applications across the supply chain.

5. Discussion

5.1. Potential Contributions

5.1.1. To AI Education Theory

The proposed multi-dimensional framework offers a systematic approach for designing AI educational resources in domain-specific contexts. By integrating data, technology, business, and education dimensions, the framework provides a comprehensive structure that can guide the development of AI education cases across different domains (Walter, 2024; Celik, 2024).

The framework extends existing AI literacy research by operationalizing AI literacy competencies within a specific application domain. While prior research has identified general AI literacy competencies (Walter, 2024), the proposed framework demonstrates how these competencies can be developed through domain-specific, data-driven educational cases.

5.1.2. To Supply Chain Pedagogy

The proposed cases demonstrate how authentic data and advanced analytics can be integrated into supply chain education. This integration bridges the gap between theoretical supply chain models and practical data-driven decision-making (Helo & Shamsuzzoha, 2024; Shaik et al., 2024). Kolb's experiential learning theory (Kolb, 2014) provides additional theoretical support, emphasizing that learning is most effective when students engage directly with concrete experiences and reflect on practical applications.

The progressive case structure addresses the need for scaffolded learning in supply chain education, allowing students to build skills incrementally while maintaining engagement through authentic business scenarios. This approach aligns with established pedagogical principles while addressing the specific needs of data-intensive supply chain education.

5.1.3. To Case-Based Learning

The proposed approach extends case-based learning methodology by combining traditional narrative-driven cases with computational, data-driven components. This integration represents an evolution in case methodology that reflects the increasing importance of data analytics in business decision-making (Eisenhardt,

1989; Yin, 2018). Recent work by Crompton and Burke (Crompton & Burke, 2026) has demonstrated the effectiveness of technology-enhanced, data-driven learning approaches in improving student outcomes across higher education contexts through their systematic review of AI's impact on learning.

Data-rich cases offer several advantages over traditional qualitative cases. They provide opportunities for quantitative analysis, enable students to develop technical skills alongside business judgment, and allow for multiple solution approaches that reflect the ambiguity of real-world decision-making.

5.2. Comparison with Existing Approaches

The proposed framework differs from existing approaches in several important ways. First, it provides explicit integration of four dimensions that are often treated separately in existing educational resources. Many existing resources focus primarily on technical aspects without adequate attention to data authenticity, business context, or pedagogical design.

Second, the framework emphasizes progressive skill development across cases, with each case building upon previous learning. This scaffolded approach is more systematic than the standalone case format common in existing resources.

Third, the framework incorporates open-source principles, making all materials freely available for adaptation and extension. This contrasts with many existing resources that are proprietary or institution-specific.

5.3. Practical Implications

For educators, the proposed case library design provides a template that can be adapted to specific teaching contexts. The cases are designed with flexibility in mind, allowing instructors to customize difficulty levels, select specific exercises, or extend the cases with additional data or techniques. The open-source nature of the materials eliminates cost barriers and enables collaborative improvement.

For practitioners, the cases demonstrate how AI and advanced analytics can be applied to real supply chain challenges. The technical specifications provide practical guidance for implementation, while the business framing helps practitioners understand the value proposition of analytics investments.

For curriculum designers, the framework provides a systematic approach for integrating AI education into supply chain programs. The four dimensions can serve as design criteria for developing new educational materials or evaluating existing ones.

5.4. Limitations

As a conceptual framework proposal, this paper has several limitations that should be acknowledged. First and most importantly, the proposed framework and cases have not been empirically validated in classroom settings. While the design is grounded in established educational principles and technical best practices, its actual effectiveness depends on implementation context and requires empirical testing.

Second, the case library is limited to three supply chain domains. Additional cases covering procurement, manufacturing, sustainable supply chain management, and other areas would strengthen the library's comprehensiveness.

Third, the datasets used are from specific time periods and geographic contexts. While this is appropriate for educational cases, it may limit the generalizability of specific findings and techniques.

Fourth, the proposed cases assume a certain level of technical prerequisite knowledge. Adapting the cases for students with different backgrounds may require additional scaffolding or preparatory materials.

5.5. Future Research Directions

Several directions for future research emerge from this work. Classroom implementation studies are needed to evaluate the framework's effectiveness in developing student learning outcomes. These studies should measure both technical skill development and business acumen, comparing the proposed approach with alternative educational methods.

Cross-cultural validation studies would test the framework's applicability in different educational contexts. Cultural factors, institutional structures, and industry environments may influence the effectiveness of specific case designs.

Expansion of the case library to cover additional supply chain domains would increase its comprehensiveness and utility. Cases addressing sustainable supply chain management, procurement analytics, manufacturing optimization, and global trade are under consideration.

Industry partnerships could provide access to current, real-time data and authentic business challenges. Such partnerships would enhance case authenticity and provide students with exposure to cutting-edge industry practices.

Development of adaptive learning versions of the cases could personalize the learning experience based on individual student needs and progress, potentially improving learning outcomes for students with diverse backgrounds.

6. Conclusion

This paper proposes a conceptual Supply Chain AI Education Case Library comprising three data-driven educational cases and a multi-dimensional framework integrating data, technology, business, and education dimensions.

The primary contributions of this work are:

- 1) A multi-dimensional conceptual framework for designing AI education cases in supply chain management, providing systematic guidance across four critical dimensions.
- 2) Three detailed educational case designs spanning supply chain domains from inventory management to logistics optimization to risk assessment, with progressively increasing complexity.
- 3) An open-source educational resource design that can be adopted and adapted by educators worldwide, contributing to the democratization of AI education.

As a conceptual proposal, empirical validation through classroom implementation is the critical next step. The framework is intended to provide a scalable template that can be extended to other domains and educational contexts. By making the case library design openly available, we aim to foster a community of educators and practitioners committed to advancing AI education in supply chain management.

The growing importance of AI in supply chain operations creates an urgent need for educational approaches that prepare students for the challenges and opportunities of data-driven decision-making. The proposed framework and cases represent a step toward meeting this need, providing a foundation for future development and empirical validation.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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