



AI-Driven Digitally Immersed Learning for the Future of Supply Chain Innovation

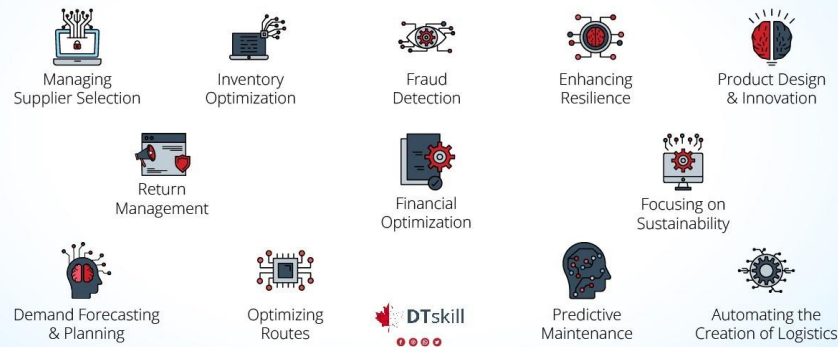
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Imagine the Future of Supply Chain Learning...

- AI is transforming supply chains. But are we preparing students for this reality?
- The future of supply chain leadership belongs to those who can harness AI effectively.

Use cases of **Generative AI** in Supply Chain



<https://www.linkedin.com/pulse/use-cases-generative-ai-supply-chain-dtskill/>

The Problem: Education is facing a rapid evolution

- Industry now runs on AI
- Without AI-driven learning, we risk a skills gap.
- Students must learn using real-world AI tools, not just theory.

The Solution: AI-Driven Learning

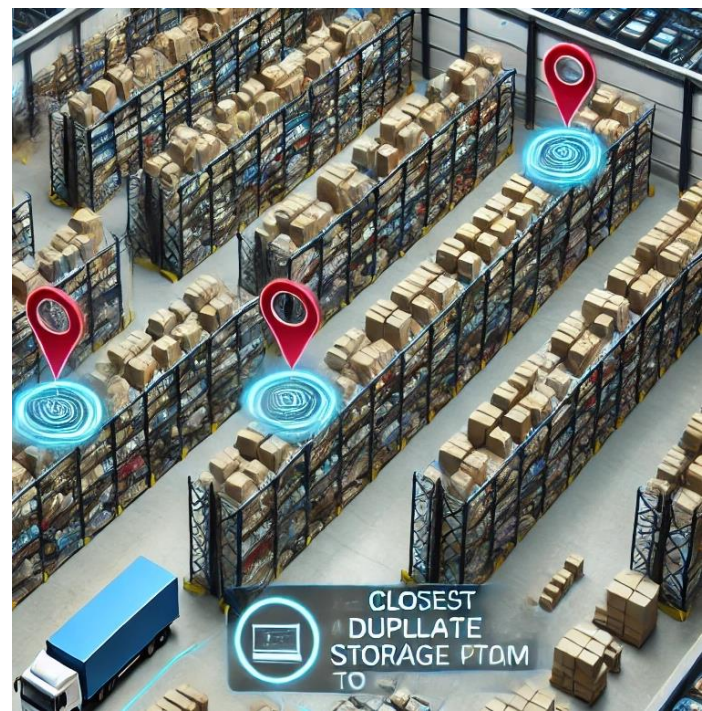
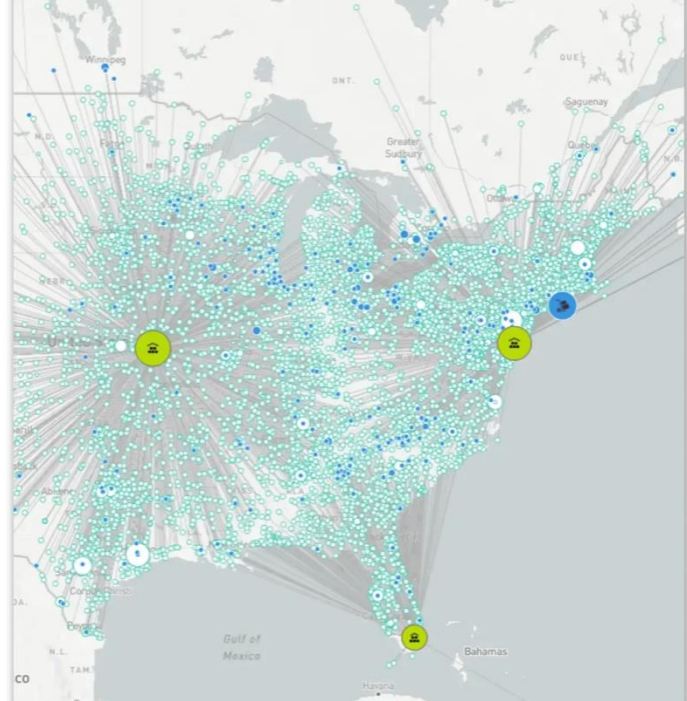
- ◆ AI-Generated Video Lectures
- ◆ Augmented Reality & Digital Twins for hands-on learning
- ◆ AI-powered Logistics & Transportation Modeling



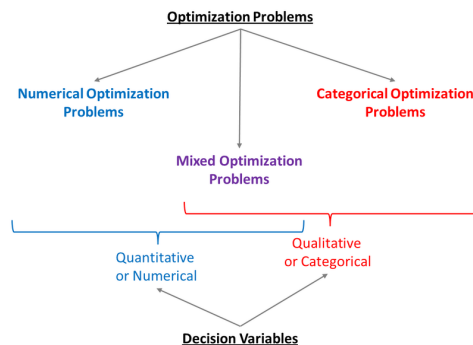
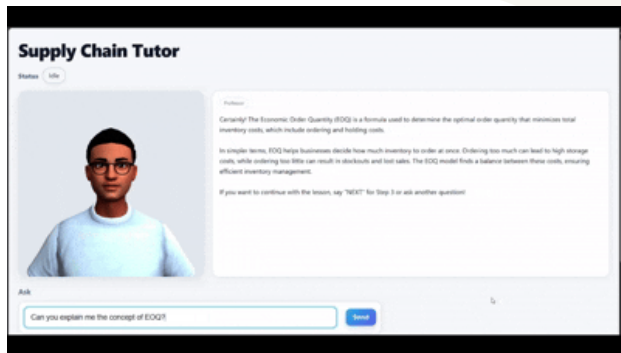
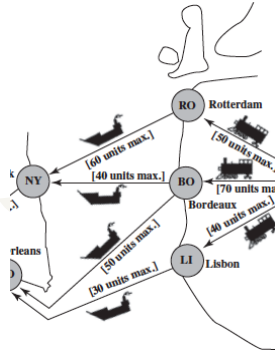


What We've Achieved So Far

- ☒ AI-driven courses in Supply Chain Innovation
- ☒ AI-driven Digital (cartoon-like) Avatar pilot in Supply Chain Management
- ☒ Successful industry and investor engagement for deploying AI-Tutor/lectures



Example: Scenario 1 – Building a mathematical constraint for Sustainable Transportation – FLOW CONSERVATION



- Showing only how to build one constraint in this example. Understanding that we have decision variables:
 - Container Flow Quantity Variable
 - Binary Movement Activation Variable
 - Intermodal Transfer Activation Variable
 - Dwell Time Variable
 - Tank-to-Wheel Emissions Variable
 - Exogenous Flow Parameter (Treated as a Variable in Constraint)
- We also have the parameters (known values) for building the proposed equation:
 - Distance Between Nodes by Mode
 - Travel Time Between Nodes by Mode
 - Tank-to-Wheel Emission Factor
 - Transport Cost Per Arc by Mode and Container Type
 - Maximum Arc Capacity by Mode and Time
 - Container Weight by Type
 - Carbon Price Per Unit Emission by Container Type
 - Transfer Cost at Intermodal Nodes
 - Dwell Cost by Node, Time, and Container Type

Output – Flow conservation constraint

Flow conservation (with dwell) — for all $i \in N$, $k \in K$, $\tau \in T$

$$\underbrace{y_{ik,\tau-1}}_{\text{inventory carried in}} + \underbrace{\sum_{(j,m,t,k) \in \Omega_{\text{in}}(i,\tau)} x_{jimkt}}_{\text{flows that arrive now}} + \underbrace{q_{ik\tau}}_{\text{exogenous net supply (+) or demand (-)}} = \underbrace{y_{ik\tau}}_{\text{inventory carried out}} \quad (\text{FG}) \quad \underbrace{\sum_{(i,j,m) \in A} x_{ijmkt}}_{\text{departures now}}.$$

Explanation (why each term is here)

- **Left side = what's available now at (i, τ) :**
 - (i) containers you had at the end of last period, $y_{ik,\tau-1}$;
 - (ii) containers that **physically arrive** at time τ after traveling their mode-specific Δ ;
 - (iii) any external injections/withdrawals, $q_{ik\tau}$ (positive adds supply; negative removes to meet demand).
- **Right side = where it goes now:**
 - (i) you may keep some to the next tick as end-of-period inventory $y_{ik\tau}$ (this is your **dwell**);
 - (ii) you may **depart** some on outgoing arcs at the current time τ .

This equality enforces—for each node, hour, and container type—that outbound and inbound flows (plus inventory dynamics) are perfectly balanced with any exogenous supply/demand. It guarantees (1) valid movement history, (2) supply/demand respect at each node-time, (3) no disappearance/duplication of containers, and (4) a physically traceable solution.

Watch the AI interaction that helped create this equation [here](#).

Join Us in Transforming Supply Chain Education!

- We are shaping the future of AI-driven learning.
- Let's make AI-driven learning a defining strength of SDSU.
- Let's build a world-class AI-driven learning experience that prepares students for tomorrow's supply chain industry—today!

Thank you!

