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An International Workshop Report on the Application of Artificial Intelligence in Supply Chain Management: Opportunities and Challenges

Boonserm Kulvatunyou
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Boonserm Kulvatunyou
Perawit Charoenwut
Systems Integration Division
Engineering Laboratory

Yen Mai
Faculty of Computer Science
Technical University of Chemnitz

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Author ORCID iDs
Boonserm Kulvatunyou: 0000-0002-7429-473X
Perawit Charoenwut: 0009-0006-5078-5469
Yen Mai: 0000-0003-9558-2743

Contact Information
boonserm.kulvatunyou@nist.gov
perawit.charoenwut@nist.gov
yen.mai.thi@fh-zwickau.de

Abstract

Artificial Intelligence (AI) has progressed significantly and impacted various aspects of our daily lives. With its strength in prediction, AI is considered a powerful tool for assessing and managing risks because it can take into account a large amount and variety of data. Global supply chains, in recent years, have been exposed to dramatic volatility and uncertainty due to a variety of natural and artificial causes. Therefore, managing supply chains becomes an increasingly serious dimensional problem where AI could play a crucial role. This motivated us to organize a workshop on the “Application of AI in Supply Chain Management (SCM)” at the 2025 International Conference on Advances in Production Management Systems (APMS) in Kamakura, Japan. The workshop was designed as a working session with the aim of gathering ideas and opinions from participating experts on what AI might contribute to the SCM processes and identifying their maturity stage and research opportunities. This paper summarizes the keynotes and the outcomes of the workshop.

Keywords

Artificial Intelligence; Supply Chain; Manufacturing.

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Preface

Workshop Organizers

Boonserm Kulvatunyou, National Institute of Standards and Technology, USA

Perawit Charoenwut, National Institute of Standards and Technology, USA

Yen Mai, Technical University of Chemnitz, Germany

Thorsten Wuest, University of South Carolina, USA

Ralph Riedel, Zwickau Applied Science University, Germany

Keynote Speakers

Soundar Kumara, Pennsylvania State University, USA

Stephen Wing, Electronic Data Exchange, Merck KGaA Life Science Business, Germany

Jae Kim, Devices and Services Product Group, Google, USA

Jo Wessel Strandhagen, SINTEF-Technology Management, Norway

Contributing Workshop Attendees

Abachiara Boffelli, University of Bergamo, Italy

Alexandra Lagorio, University of Bergamo, Italy

Boonserm Kulvatunyou, National Institute of Standards and Technology, USA

Christoph Roser, Karlsruhe University of Applied Sciences, Germany

David Romero, Tecnológico de Monterrey, México

Farhad Ameri, Arizona State University, USA

Gregor von Cieminski, ZF Friedrichshafen AG, Germany

Jan Ola Strandhagen, Norwegian University of Science and Technology, Norway

Jo Wessel Strandhagen, SINTEF-Technology Management, Norway

Jannicke Baalsrud-Hauge, KTH Royal Institute of Technology, Sweden

Perawit Charoenwut, National Institute of Standards and Technology, USA

Stephen Granite, National Institute of Standards and Technology, USA

Tasuku Sato, Mitsubishi Heavy Industries, Ltd., Japan

Thorsten Wuest, University of South Carolina, USA

Vittaldas Prabhu, Pennsylvania State University, USA

Yen Mai, Technical University of Chemnitz, Germany

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Author Contributions

Author 1: Conceptualization, Supervision, Writing- Original draft preparation. **Author 2**: Data curation, Formal analysis, Writing- Original draft preparation. **Author 3**: Data curation, Formal analysis, Writing- Original draft preparation.

1. Workshop Format

The workshop was organized in a hybrid manner, in which the participants partaken on-site at the APMS conference, and experienced a four-hour workshop including keynotes and brainstorming sections. While the 20-minute keynotes were delivered both online and in-person, participation in the brainstorming section was limited to in-person. The main objectives of the keynotes section were to give the participants (i) the context of what AI means today and in the near future, and (ii) the context of supply chain problems currently encountered in industry. For the first objective, Prof. Soundar Kumara from Penn State University (USA) delivered the history and the outlook of AI. For the second objective, keynote presentations were delivered by experts from three different industries: biopharma, electronics, and shipbuilding. The biopharmaceutical industry was covered by Mr. Stephen Wing from Merck KGaA (Germany), the electronics industry by Dr. Jae Kim from Google (USA), and the shipbuilding industry by Dr. Jo Wessel Strandhagen from SINTEF (Norway). After the three keynote speeches, the workshop continued with the brainstorming section, in which a digital interactive brainstorming board was pre-designed and used for collecting, normalizing, and concluding inputs from all the participants. The brainstorming section was limited to in-person participation and lasted for two and a half hours. The process of the brainstorming section is summarized in Fig. 1. The details are given as follows.

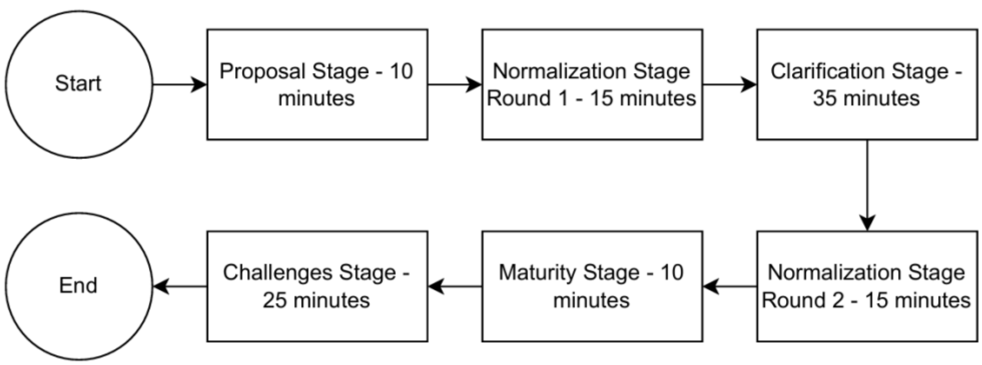

Fig. 1. The process of the brainstorming section

Proposal Stage: Participants were given 10 minutes to write down up to three ideas about the application of AI to address supply chain issues and tagged them with SCOR high-level processes [1], namely: Plan, Source, Make, Delivery, or Return (more than one tag could be assigned). They also tagged it with one of the three types of issues most relevant to it, namely: (i) Operation, (ii) Security, or (iii) Regulatory Compliance. Participants use a digital “post-it” to lay out their ideas on the digital interactive brainstorming board according to the SCOR process tags and use the tagging mechanism to assign the issue type. Figure Fig. 2 shows the blank digital brainstorming board. It should be noted that the ideas relevant to more than one SCOR process are placed along the side or in the middle diagonal or center area to indicate such a situation. This gives a better visual cue for that categorization than using the tagging feature.

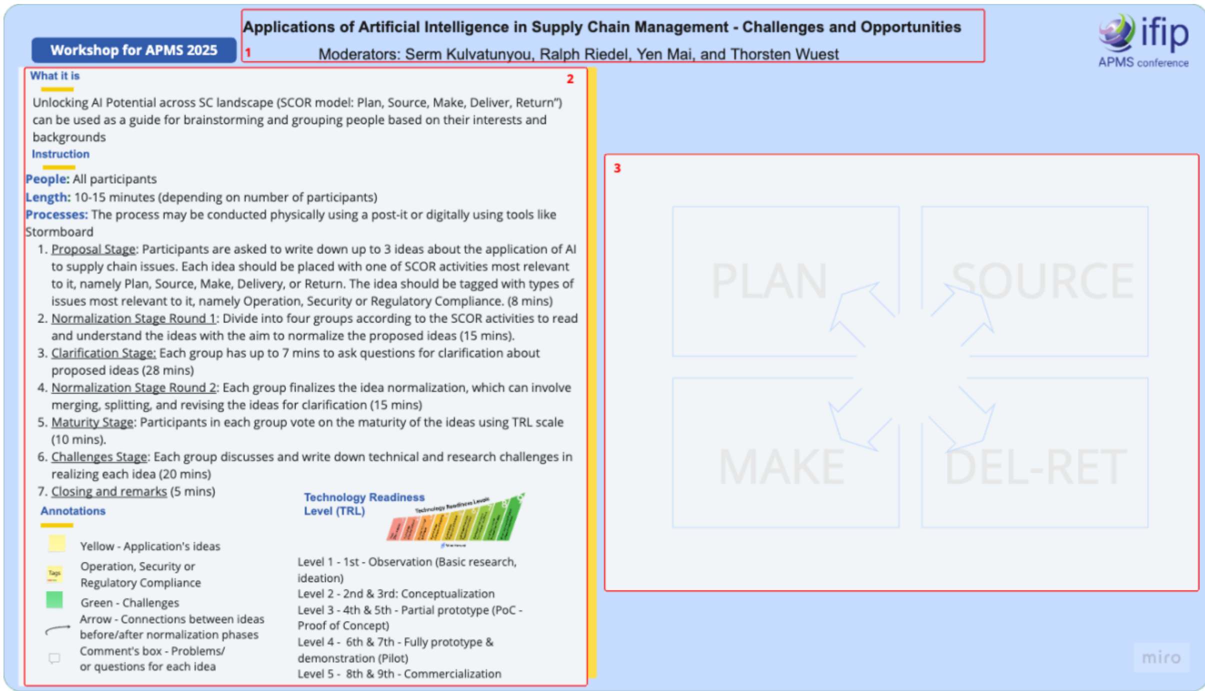

Fig. 2. Blank digital brainstorming board

Normalization Stage Round 1: In this second stage, participants are divided into four groups according to the SCOR processes: Plan, Source, Make, and together the Delivery and Return, to read and note down any clarification questions about the ideas tagged by those processes. Participants may also get clarifications about ideas given by members in the same group. They may also group post-its with similar ideas for easier analysis in subsequent stages. Fifteen minutes were given to the groups.

Clarification Stage: In this third stage, each group is given seven minutes to ask questions about their ideas posted by other groups for the clarification they need.

Normalization Stage Round 2: In this normalization stage, each group is given 15 minutes to finalize their ideas normalization, which can involve merging, splitting, and revising their ideas for clarity. Arrows are used to connect original and revised or derived ideas to keep traceability. After this process, surviving ideas are normalized and ready for maturity level labeling.

Maturity Stage: In this stage, participants are given 10 minutes to vote on the maturity of AI technology to support each idea using the Technology Readiness Level (TRL) framework developed by NASA [2]. Participants vote on all ideas. However, the original nine levels are re-formulated into five levels so that the process is easier and faster, in that the participants would need less time to comprehend and choose in case they are not familiar with the nine TRL levels. For this reason, the first TRL level is kept but renamed as “Observation” (Basic research, ideation), while levels 2 and 3 are merged as “Conceptualization”, levels 4 and 5 as “Partial prototype” (PoC - Proof of Concept), levels 6 and 7 into as “Fully prototype & demonstration” (Pilot), and the last two levels, levels 8 and 9 as “Commercialization”.

Challenge Stage: In this last stage, participants in each group work on identifying challenges in realizing the ideas located in their respective areas. They are given 10 minutes to work on this task. The participants have diverse research backgrounds. However, they have common research focused on supply chain management and operations management research topics. Some of them have a background in AI work. In total, there were 15 participants contributing to the brainstorming section.

2. Summary of Keynote Presentations

2.1. "How AI is Changing Everything" – What Local Leaders Need to Know to Prepare, Benefit, and Stay Relevant

Speaker: Prof. Soundar Kumara, Allen E. Pearce and Allen M. Pearce Professor of Industrial Engineering, Department of Industrial and Manufacturing Engineering, Pennsylvania State University, USA

Summary: Prof. Kumara kicked off the workshop by giving the history and the future outlook of AI. He then highlighted two recent AI application projects he had led. Prof. Kumara recapped the history and future of AI from a futuristic perspective, as well as from an implementation view with two specific implementations: he addressed the three waves of AI and the three types of AI, discussed some AI challenges, and showcased recent projects. The three waves of AI are (i) knowledge base, (ii) neural network, and (iii) neuro-symbolic AI. Knowledge-based AIs are rule-based systems that utilize logic and reasoning. They are predominantly symbolic AI systems. Neural Network (NN) AIs have evolved from the 1990's multi-layer perceptron models to today's convolutional models, also known as Deep Learning or Deep NN (DNN). The near future of the NN AIs will be enhancements related to increasing the explainability of the output and the personification of the AI into agents collaborating together, known as "Agentic AI". While DNNs are very powerful, they lack common sense, formal knowledge, and logical reasoning and can be easily fooled. Therefore, the next wave of AIs will put the two waves together into a "neuro-symbolic AI" exploiting the best of both. The three different types of AI with increasing levels of intelligence are (i) Narrow AI, (ii) General AI, and (iii) Artificial Super Intelligence. The characteristics of them are summarized in Table 1. He concluded that the evolution of AIs over the next 10 years will see the rise of agentic AIs and democratization of AIs that will require a workforce transformation, and while their potentials are enormous, there will also be issues related to required energy and associated environmental and societal impacts that will lead to ethical and regulatory complications.

Table 1. Three types of AI and their properties – Prof. Soundar Kumara (2025)

Types of AI	Properties
Narrow (Weak) AI	Task-specific.
	No consciousness or self-awareness.
	Rule-based or data-driven.
General AI (Strong AI)	Human-level intelligence.
	Cross-domain knowledge.
	Autonomous learning.
Artificial Super Intelligence	Beyond human capability.
	Potential for self-improvement.
	Advanced problem solving.

Prof. Kumara then went over his two recent AI projects, both utilized a combination of agentic AI, graph database, Retrieval Augmented Generation (RAG), and edge computing. The first provides a chatbot for welding quality assurance and workforce training that is able to guide the user with the classification and explanation of welding quality based on images. The bot learns from a variety of data, including images, workers' knowledge (graph), and general manufacturing knowledge. The other project[1] provides a chatbot for supply chain information query and analysis about dairy farmers and producers. It learns from publicly available data and incorporates Geographical Information System (GIS) data and presentation. While still lacking capacity and supply chain relationship data, the system has shown benefits such as profitability increase, local sourcing, and regulatory compliance to farmers, processors, manufacturers, and policymakers. The two projects are summarized as supply chain challenges and AI applications in Table 2.

Table 2. Challenges and potentials of AI in manufacturing and supply chain sectors

Supply Chain Challenges	Potential AI Application
Real-time quality control at the manufacturing level & Workforce training (Welding sector).	Use Graph Database, agentic AI, and Edge computing to enable knowledge mining from real-time manufacturing data.
Strategy supply chain planning and sourcing (Food sector).	Use Graph retrieval-based Agentic AI to connect producers, processors and policy makers with food manufacturers.

In conclusion, Prof. Soundar Kumara provided an overview of how AI had been changing the world in multiple aspects. The speech included the potential of AI at the present and in the future, as well as the challenges AI might bring as it evolves and gets adopted. Two use cases from different sectors were provided that demonstrated the suitability of Graph DB compared with relational DB when used with agentic and RAG AI models. Finally, ethics, regulation, and resource consumption are foreseeable challenges to overcome.

2.2. Transforming Biopharma SCM with AI – Key Supply Chain Challenges in Biopharmaceutical Manufacturing

Speaker: Mr. Stephen Wing, Principal Business Development Manager, Electronic Data Exchange, Merck KGaA Life Science Business, Germany

Summary: Stephen's business unit represents the supply side of the industry. It supplies both discrete manufacturing items, such as bioreactor bags and process manufacturing items like cell culture media. In his purview, the biopharmaceutical industry as a whole is undergoing digital transformation, driven by Industry 4.0 initiatives, with key objectives centered on simplifying and optimizing business processes. The biopharmaceutical product lifecycle consists of seven complex operational phases, including (i) drug discovery, (ii) process development, and (iii) clinical trials, continuing into (iv) scale-up and (v) commercial manufacturing, and finally, (vi) launch support and (vii) patient feedback. The clinical trials, scale-up, and commercial manufacturing phase are where SCM plays a critical role. Based on this, Mr. Wing described SCM challenges in two aspects: the system aspect and the operational aspect. In the system aspect, he emphasized the heterogeneities in business processes and applications, operating

[1] https://grass-sigma.vercel.app/

systems and tools, functions and resources, including people, diverse data and data flow requirements, and enterprise platform eco-system as challenges. He wondered how AI may help address these challenges, but also mentioned that standardizing this heterogeneity, especially the data and enabling electronic data exchange across the enterprise and supply chain, could address the challenge and also help enable AI. In the operational aspect, he described the SCM challenges in six areas and gave ideas on how AI may be applied to them as follows:

Table 3. SCM challenges and potential AI applications in Biopharma

Supply Chain Challenges	Potential AI Applications
Demand Forecasting and Inventory Optimization: **High demand variability for custom products and risks of stockouts or overstocking.**	Use AI predictive analytics and simulation to dynamically manage inventory.
Supply Chain Visibility and Risk Management: **Limited visibility into multi-tier supply chains and vulnerability to disruptions.**	Apply AI-powered real-time monitoring dashboards and risk prediction models to identify potential disruptions early and enable proactive mitigation.
Cold Chain Management: **Maintaining strict temperature controls and high spoilage risks during transport and storage.**	Use IoT-driven AI monitoring to detect and predict temperature excursions in real-time and predictive maintenance to forecast equipment failures before they occur.
Manufacturing Process Optimization: **Production inefficiencies and high batch variability in complex biologics.**	Apply digital twins and AI-driven real-time optimization models to predict and prevent process variability with automated adjustments.
Regulatory Compliance and Quality Assurance: **Complex global regulatory requirements and non-compliance risks from manual errors.**	Use AI-powered automated documentation and analysis tools to create regulatory filings and analyze production data to identify potential Good Manufacturing Practice (GMP) deviations.
Waste Reduction and Sustainability: **High waste levels from expired materials and inefficient processes, plus pressure to meet sustainability targets from energy-intensive cold storage and single-use equipment.**	Apply AI-driven process adjustments to reduce material waste and use sustainability analytics to track carbon footprints and suggest eco-friendly alternatives.

Across all six areas, he predicted that AI applications can deliver benefits including cost savings through reduced inventory, waste, and regulatory compliance expenses; improved operational efficiency via enhanced forecast accuracy, faster time-to-market, and reduced lead times; enhanced quality and reliability through better quality monitoring and fewer recalls; and strengthened risk mitigation by proactively preventing disruptions, material shortages, and equipment failures. In closing, Mr. Wing anticipated that as drug molecules become more complex, such as those using antibodies, cell biologics, and personalized medicines, supply chain management complexity will increase. Therefore, AI can play an even more essential role in the biopharmaceutical industry.

2.3. Challenges and Opportunities in Applying AI in Supply Chain – Google's Practical Best Practices for the Industry

Speaker: Dr. Jae Kim, Senior Software Engineering Manager, Devices and Services, Google, USA

Summary: Dr. Kim explained the responsibilities and goals of his working group, called "Devices & Services Product Group (DSPG)". DSPG provides products and services to businesses and consumers. His responsibility is to develop Devices and Services (D&S) Systems that encompass productivity software solutions to support nine functional areas in DPSG, including customer support, product design, sourcing, product operations, manufacturing and supply chain of products, planning and fulfillment, fulfillment and execution, and finance. For those, Dr. Kim described AI applications in the supply chain in four challenging areas, including (i) enhancing customer experiences, (ii) driving up efficiency and sustainability in operations, (iii) delivering resiliency and reliability of products and services, and (iv) enabling seamless collaborations across Google's global business. These are summarized in Table 4 below. Finally, he went over the technological challenges of employing AI. He provided challenges associated with different types of AI technologies, summarized in Table 5; challenges associated with AI risks and ways to deal with them, summarized in Table 6; and challenges associated with different approaches in dealing with data heterogeneity, summarized in Table 7.

Table 4. A summary of supply chain challenges and AI applications in Google's businesses

Supply Chain Challenges	AI Applications	Maturity
Ensure exceptional customer experiences	Use deep learning on complex datasets for accurate supply and demand forecasting to ensure product availability. Complex datasets include many kinds of data, such as time series data, product attributes, location attributes, historical inventory data, historical weather data, promotions, events, holidays, store information, and demand signals.	Deploy
	Use advanced AI tools and pipelines to enhance forecast explainability, e.g., using SHAP (SHapley Additive exPlanation) values and providing multi-dimensional visualization between key drivers and the forecast.	Deploy
	Use AI for customer segmentation and deliver tailored products and services.	Deploy
	Use Generative AI (GenAI) to summarize conversations and automate customer service tasks.	Deploy
Drive efficient and sustainable operations	Use AI for fleet routing and operation optimization.	Experiment
	Use GenAI with RAG/GraphRAG for intra-knowledge question & answer based on disparate data across the supply chain and internal documentations such as manuals and standard operating procedures.	Experiment
	Use GenAI on complex enterprise application data such as contracts, sales orders, fulfillment orders to allow for quick navigation across these large, disparate datasets.	Experiment
	Use GenAI to continuously search and summarize complex global regulations to speed up and automate compliance.	Deploy
Deliver resiliency and reliability of production and supply chain	Use AI to enhance quality control.	Vision
	Use AI to enhance end-to-end visibility and optimize production at scale.	Vision
Global team collaboration and data accessibility across supply chain	Use AI to enhance employee collaboration and data accessibility across the globe	Experiment

Table 5. Summary of different AI technologies and their challenges

AI Technology	Data Challenge	Usability Challenge
Traditional ML	Cost and efforts needed to clean and merge data across silos.	Hard to trust and justify decisions due to the lack of explainability.
GenAI	Risk of exposing sensitive data. Risk from bias data.	Risk of factually incorrect outputs, such as wrong delivery dates, and bias due to hallucinations and unbalanced data.
Knowledge Graph (used by itself or with other AI technologies)	Cost and efforts needed to standardize data, and to map from silos	Lack of buy-in and resistance to change to use standard, non-localized terminology.

Table 6. Summary of AI risks and remedies

AI Risk	Remedy
Not performing as intended (e.g., safety, quality, accuracy)	Define safety attributes, check recitations, provide feedback channels, and moderate content.
Misapplication and/or harmful use	Provide terms of service and acceptable use policy, monitor safety attributes, and restrict access and use of privacy data.
Creating an impression of having capabilities it does not possess	Provide caveats and disclaimers, an acceptable use policy, and model cards to inform users.
Creating or amplifying negative biases, harmful and non-factual information, and unsafe/immature models	Ensure proper bias and safety attribute evaluations of models, compliance with the Responsible AI (RAI) guide and acceptable use policy, and monitor model drifts.

For the data heterogeneity (see Fig. 3 for different kinds, formats, and sources of data needed to be considered by AI), Dr. Kim specifically emphasized the use of Knowledge Graph with RAG technology to enhance the performance of the Generative AI (GenAI), which is together called GraphRAG. He concluded that while GraphRAG is not perfect either, Google's implementation shows enhanced accuracy.

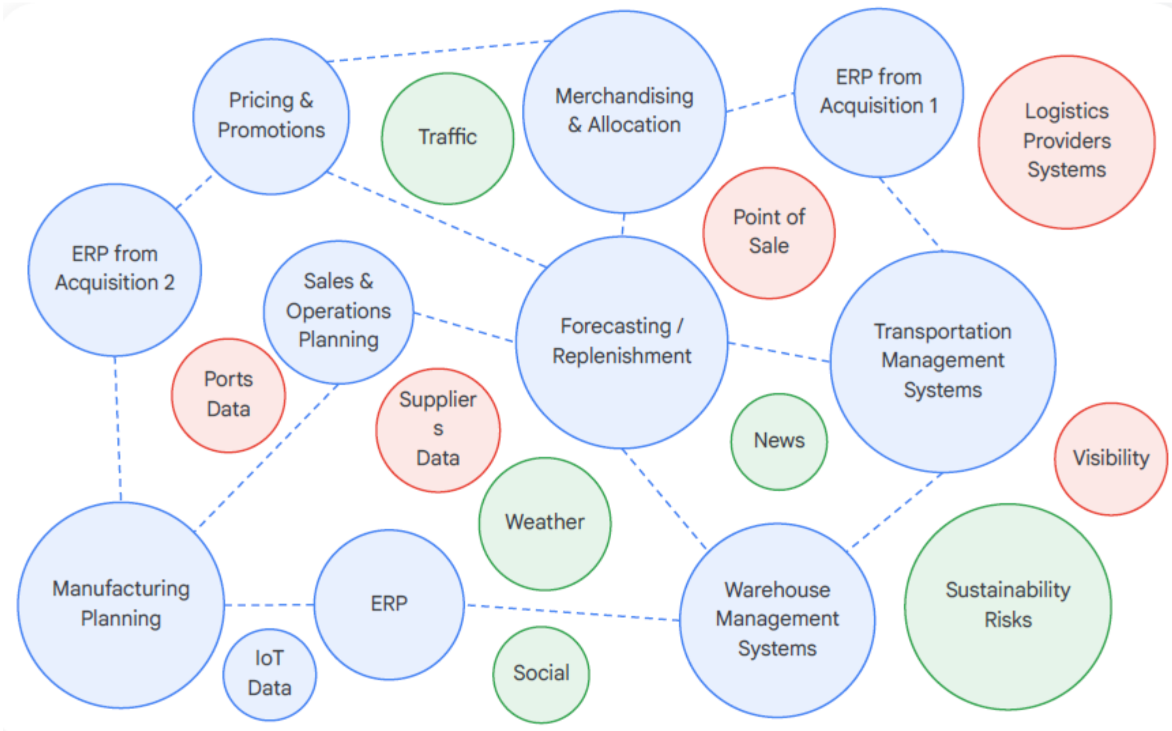

Fig. 3. Variety of data influences supply chain planning and operation.

Table 7. Summary of approaches for dealing with data heterogeneity

Semantic Layer Approach	Approach Description	Challenge
No knowledge graph	Vectorize unstructured data. Simplify structured data into flat, denormalized data. Link structured data to metadata and explicit business process and object relationship models to provide context meaning.	Need human efforts to simplify data structure, and develop and link metadata and models. No formal, logical reasoning support.
Non-native knowledge graph	Generate a virtual knowledge graph using Ontology-based Data Access (OBDA) methods such as R2RML, Ontop, and in-memory LLM-generated dynamic mapping.	Need to develop the ontology standard.
Native knowledge graph	Translate structured data into a knowledge graph at rest. Use W3C standard RDF OWL/RDF graph with SPARQL query language or Labeled-Property Graph (LPG) with Google's Spanner Graph DB or emerging standards such as GQL query language.	Need to develop the ontology standard. LPG query support is still largely proprietary.

2.4. AI in the Yard Industry

Speaker: Dr. Jo Wessel Strandhagen, Research Scientist, Technology Management, SINTEF, Norway

Summary: Dr. Strandhagen first presented the general process of customized shipbuilding. Then, he described challenges in the process and potential AI applications. He then described an ongoing project to develop digital twins and AI tools to support the operationalization of a shipyard to support the construction and maintenance of offshore windmill construction and operation. Using that context, he provided another set of challenges and potential AI applications. Details of these two aspects of the presentation are summarized below. The process in customized shipbuilding includes design, planning and coordination, engineering, procurement, production, and after-sales activities. These activities overlap in time and sequence of major milestones, including, in chronological order, contract signing, start of production, launching and start of on-boarding activities, and delivery. During this process chain, operational and managerial processes face several challenges, such as transport, coordination, work management, and those summarized in the first column of Table 8. Respectively, the potential applications of AI to address these challenges are identified in the second column.

Table 8. Challenges in customized shipbuilding and potential applications of AI

Challenges in the Yard industry	Potentials of AI Applications
Transport: Extensive internal transport with many empty or out-of-sequence moves.	Use AI to create a Real-Time Location System (RTLS)-driven dynamic routing and dispatching system for forklifts or transporters to cut empty runs and smooth peaks.
Coordination: Logistics must be coordinated within and across parallel projects sharing resources.	Apply AI-based multi-project scheduling and multi-agent negotiation to resolve crane, space and crew conflicts automatically.
Work management: Daily orchestration leans on experience, gut feel and tacit knowledge.	Provide a shop-floor copilot—Retrieval Augmented Generation (RAG) over Standard Operating Procedures (SOPs), reports and change orders—that proposes next actions and explains the why.
Walking time: Long distances translate into non-value-adding walking.	Use location-aware and AI-based task assignment and layout simulation to shorten walking and place materials closer to the point of use.
Information flow: Relevant information is fragmented across systems, drawings and messages.	Use AI to summarize change orders and discussions; link Bill of Materials (BOM), Work Breakdown Structure (WBS) and 3D drawings in a navigable knowledge graph with targeted alerts.
Personnel mobilization: Mobilizing and demobilizing large crews over months, including housing and facilities, is hard.	Use AI to forecast demand by milestone and optimize shifts, onboarding windows and accommodation plans.
Material reception: Inbound volumes and sequences often don't match assembly needs.	Use AI to predict Expected Time to Arrivals (ETAs), and automatically schedule appointment slots and slot docks/yard space in the assembly sequence.
Inventory & space: Large and highly variable inventory and space needs by project.	Use AI to forecast project-specific inventory and allocate space dynamically, including 3D bin-packing for halls and yards.

Warehouse operations: Heavy volumes and crowded areas make free space hard to find.	Use AI to recommend the best locations on a live yard map, backed by drone/vision counts to keep locations accurate.
Material control: High variety and early orders create intermediate storage and WIP build-ups.	Use AI to tune inventory policies, trigger pull signals tied to schedule risk and show kitting readiness before release.
Material handling: Large, heavy items need maneuvering space and scarce crane windows.	Use AI to schedule cranes/gantries, plan safe paths with geofencing, and recommend the best lift windows.
Material flow: Flows are complex across the yard and within halls, stores and stages.	Use a discrete-event digital twin and AI-based process mining from ERP/MES/RTLS to find bottlenecks and test what-ifs.

Dr. Strandhagen then talked about the current TWinYards project he is involved in. It aims to operationalize a shipyard to supply offshore windmill substructures, platform structures, and ships for building and operating offshore windmills. The project is challenged by the need to improve cost and productivity by 10-15% and is looking into using digital twins and AI to enable such improvement. The summary of project challenges and potential AI applications is provided in Table 9.

Table 9. Challenges in operationalizing the shipyard to support offshore windmill construction and operation, and potential AI applications

Challenges	Potential AI applications
Yard Operations Resource Planning	Use AI to create a Real-Time Location System (RTLS)-driven dynamic routing and dispatching system for forklifts or transporters to cut empty runs and smooth peaks.
Area Utilization Planning and Material Flow	Use digital twins and AI to enable dynamic planning, monitoring, simulation, prediction, and optimization of movement and area allocation through production stages, and prevent conflicts.
Production Hall Planning and Internal Flow	Use AI to enhance forecasting, optimization, and decision-making for anticipated bottlenecks and resource constraints, and use digital twins to simulate and analyze scenarios to support planning to achieve continuous improvement of operational strategies.
Workforce Planning	Use AI and digital twins predictive analytics to forecast personnel needs, detect anomalies for overtime and compliance risks, identify skill gaps, provide insights to balance workloads and run scenario simulations for optimized workforce planning and scheduling.
Incoming Materials Management	Leverage digital twins and AI to monitor and predict incoming material flows, delays and quality issues, and provide actionable insights and optimal coordination between logistics and production.
Engineering Design Change Impact Analysis	Use digital twins to evaluate multiple design options on how they affect existing production plans and use AI to proactive plan for adjustments and minimize disruptions.

Dr. Strandhagen concluded his talks with the following remarks. A common requirement to succeed in those diversified and multi-aspect shipyard projects is the Data connection and integration of systems. A combination of Digital Twins (DTs) and AI can enable the real-time modeling and prediction functions. In the end, optimization and prediction play a key role in enhancing the efficiency and quality of the project operation. In short, the applications of AI in the yard industry, as described through the TWinYards project, are very diversified and cover multiple aspects from planning to the delivery process. Furthermore, the scope of the project covers from the operational to the strategic level activities. Common requirements are found relating to data and information integration in the Yard industry, which is also a typical barrier recognized in other industries.

3. Summary of Workshop Result

3.1. AI Applications Summary from the Brainstorm Board[2]

The brainstorming section of the workshop lasted for 1.5 hours with six stages of brainstorming and normalization. The result is a brainstorm board filled with ideas classified by main SCOR processes and categories of supply chain issues, including operation, security, and regulatory compliance. In addition, challenges in realizing these ideas were identified. The state of the brainstorming board right after the workshop is shown in Fig. 4 below. While it is not readable, the figure shows that many ideas were identified in the yellow post-its, they are clarified and derived during the normalization as indicated by the arrows connecting them, and challenges were noted in the green post-it and linked to the ideas. At the end of the workshop, there were still typographical errors and duplicates that the organizing team post-processed to clean up. The data were then exported to an Excel file for further analysis of which the result were summarized in Table 10 below.

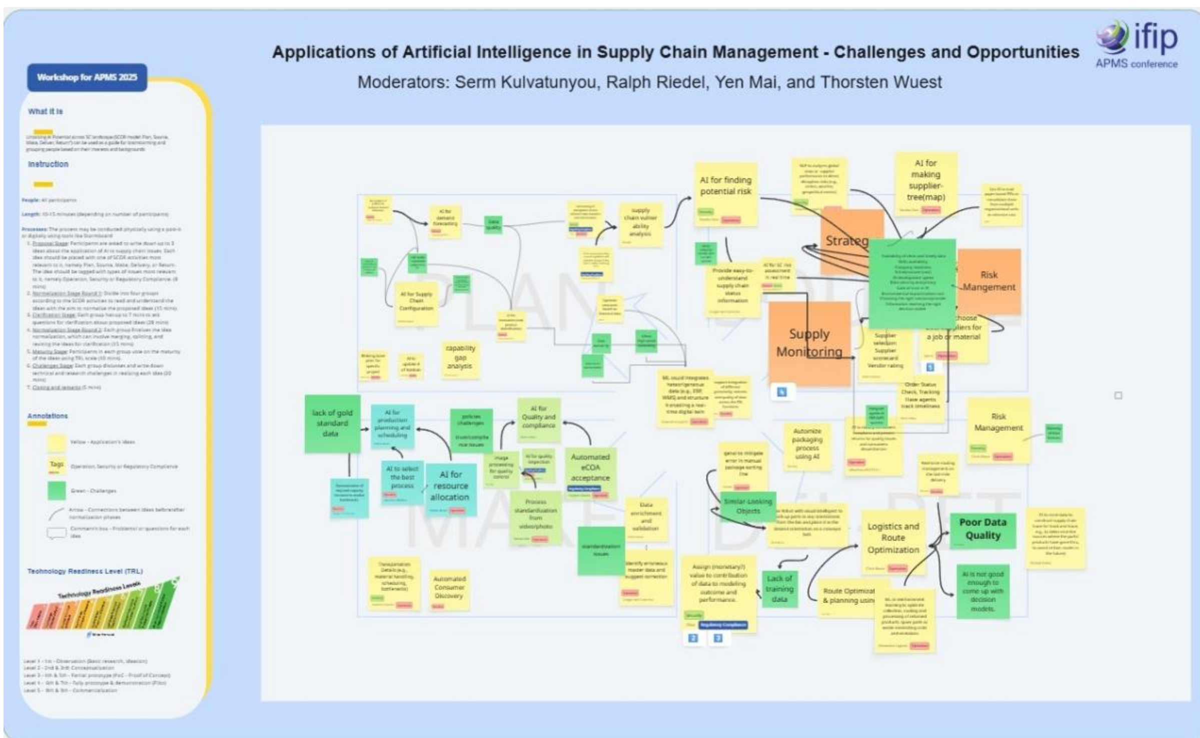

Fig. 4. Filled digital brainstorming board with ideas from participants

In Table 10, “O”, “S”, and “R” represent the three categories of SCM issues: Operation (O), Security (S), and Regulatory Compliance (R), respectively. “NA” is for the uncategorized case. In the Challenge column, U means undefined. This may not be because there is no challenge, but

[2] The board can be found at https://miro.com/app/board/uXjVJfz_5F4=/?utm_source=notification&utm_medium=email&utm_campaign=daily-updates&utm_content=board-name&lid=63hegkhdbhnq

there was insufficient time. The Simplified TRL column shows the mean value calculated from participants' votes.

Table 10. Summary from the post-processed brainstorm board

SCOR Process	Application	Scope	Challenge	Simplified TRL
Plan (avg. maturity 2.8)	AI for supply chain configuration: • Forecasting of disruptions across different time horizons and supply network functions. • AI for assessment of the current regulations and potential changes in the short, medium and long term.	O, S, R	• Data quality. • High-quality/explainable output from AI.	2.7
	AI for demand forecasting: • Recognition of patterns in customer demand behavior.	O	• Lack of a standardized approach and commercial software. • How AI could understand the supply chain and business context and decide on it.	3.7
	Supply chain vulnerability analysis.	O	U	3.0
	Optimize resources based on historical data: • ML could integrate heterogeneous data (e.g., ERP, WMS) and structure it, enabling a real-time digital twin.	O	• Data availability. • Data format standardization. • (Ultra) High-speed computing.	2.0
	Capability gap analysis.	O	U	2.4
	AI for innovation (new product identification).	O	Data availability.	2.3
	Making a base plan for a specific project.	O	U	2.7
	AI to automatically update Kanban cards.	O	U	2.8
Source (avg. maturity 4.2)	**Strategy**	NA	• Availability of clean and timely data. • Skills availability. • Company readiness. • Infrastructure (cost). • AI development speed. • Data security and privacy. • Lack of trust in AI. • Environmental impact/carbon cost. • Choosing the right solution/provider. • Information reaching the right decision-maker. • Difficult to integrate AI agents with ERP/MES systems.	4.0
	Use AI to read paper-based purchase orders to consolidate them from multiple organizational units to minimize cost.	NA		3.8
	AI for supplier discovery, selection, evaluation, and rating.	O		4.3
	AI for making a supplier-tree (map).	O		4.0
	Risk Management	NA		3.8
	NLP to analyze global news or supplier performance to detect disruption risks.	O, S		3
	AI for finding potential risk.	O, S		3.5
	AI for SC risk assessment in real-time.	O, S		5.0
	Supply Monitoring	NA		4.7
	Provide easy-to-understand supply chain status information.	NA		4.5
	Order status check & tracking with AI agents.	NA		4.8
	AI for Quality and Compliance:	O, R	Policies challenges	3.0

Make (avg. maturity 2.9)	• Automated eCOA acceptance. • Quality inspection. • Image processing for quality assurance. • Process standardization.		trust/compliance issues.	
	AI for production and planning: • Select the best process. • Resource allocation. • Solving bottlenecks. • Transportation details.	O, S	Lacking of gold standard data and standardization issues.	2.8
Deliver & Return (avg. maturity 4.2)	Automate the packaging process.	NA	U	4
	AI to classify consumer complaints and prevent returns due to quality issues and consumer dissatisfaction.	O	Integrate AI agents in ERP/MES systems.	3.8
	Logistics and route optimization: • Route optimization & planning. • Real-time routing management on the last-mile delivery. • Optimize collection, routing, and processing returned products, spare parts or waste.	O	• Poor data quality. • AI is not good enough to come up with decision-making models.	3.9
	Use robots with visual intelligence to detect, place and pick up parts on the conveyor belt: • AI to mitigate errors in the manual package sorting line.	O	Similar-looking objects and a lack of training data.	4.8
All	Assign a value to the contribution of data to the modeling outcome and performance.	S, R	Lacking of training data.	2.0
	Construct a supply chain trace for track and trace.	NA	U	3.5
	Support integration of different granularities, volumes, and quality of data across the supply network functions.	O	U	2.2

In summary, the workshop gathered 32 distinct AI application ideas from participants. The Plan category received eight main ideas, achieving an average maturity of 2.8. The Source category produced eight ideas and was categorized into Strategy, Risk Management and Supply Monitoring, with the overall average maturity of 4.2. In the Make category, nine ideas were consolidated into two main ideas with an average maturity of 2.9. The Delivery and Return category got four ideas with 4.2 average maturity level. Lastly, there were three ideas that fit with all categories. Primary challenges include the need for explainable AI outputs, a lack of standards, and data availability and quality constraints.

4. Workshop Results Discussion

The workshop revealed diverse AI applications spanning all top-level supply chain processes in the SCOR model – Plan, Source, Make, Delivery, and Return, with different maturity levels. This diversity reflects differences in problem structure, data availability and organizational readiness along with AI capability requirements. Workshop participants shared their experiences and perspectives on AI applications in conversational form. It is observed that most suggested applications went beyond today's popular Large Language Model (LLM) AI. Participants are looking for more value from AI–to apply it to analytical problems that drive decision making and operational and transactional executions. However, as shown in Prof. Kumara's and Dr. Kim's presentations, LLMs may provide fundamental functions to process and also present diverse data. It should be noted that the maturity levels discussed throughout this section represent participants' collective assessments of perceived technology readiness. These ratings reflect participants' opinions based on their experiences and may not align with the state of implementations in the industry. The following sections elaborate on these insights by drawing on supply chain and AI literature to contextualize and explain the suggested applications and challenges.

4.1. Plan

The plan process represents the intelligence center of SCM, where AI could be leveraged to transform reactive, historical data-based pattern recognition systems into proactive, real-time data-based predictive systems. This transformation would address the challenges in managing resources and capabilities in the prediction of future demand rather than in response to past patterns. Workshop participants assessed planning applications at an average maturity of 2.8, suggesting they perceived these technologies in proof-of-concept stages. This moderate assessment is aligned with the challenges participants identified for this process, particularly regarding data infrastructure and the quality and explainability of the model output.

Demand forecasting, unlike traditional time-series methods that extrapolate historical trends with few variables, AI approaches would employ machine learning to identify behavioral patterns and demand indicators. These systems are expected to integrate multiple data sources (e.g. social media, weather, and economic indicators) to generate early demand signals. Supply chain network configuration applications would leverage AI to enhance strategic decisions regarding facility location, capacity allocation, and inventory management. AI-enhanced optimization could evaluate multiple objectives simultaneously while processing dynamic data and solving complex configuration problems. Vulnerability analysis applications would employ network analysis methodologies to identify critical nodes and assess failure propagation pathways. AI could be used to analyze patterns in disruption data and network structure that traditional methods might miss.

4.2. Source

Participants assessed source applications at an average maturity of 4.2, the highest maturity level, alongside delivery and return. However, AI applications in the sourcing process typically confront unique inter-organizational challenges where data access, trust establishment, and incentive alignment create barriers that technology deployment alone cannot overcome. Participants suggested sourcing strategy applications for supplier discovery, selection, evaluation, and rating. Recent GenAI developments could enable the interpretation of natural language supplier information from diverse sources, potentially expanding systematic supplier evaluation beyond traditional methods. These systems could process unstructured data from company websites, sustainability reports, and industry databases to identify potential suppliers that might be overlooked by conventional searches. However, participants noted data security and privacy as challenges constraining implementation, as supplier selection often requires access to sensitive business information, including real-time data such as capacity. Risk management applications would employ LLM to analyze financial indicators, geopolitical developments, and news sources. These applications would address a critical need in modern supply chains where disruption risks have become increasingly complex and interconnected. The ability to continuously monitor global events and translate them into supply chain risk signals would be beneficial not only for sourcing but also for building resilience across supply chains. Related supply monitoring applications could provide easy-to-understand status information through AI agents that aggregate data from multiple systems and present it in accessible formats for decision-makers at different organizational levels.

4.3. Make

Manufacturing applications are clustered around two primary themes: quality management and production planning. Workshop participants assessed both themes at moderate maturity levels at 3.0 and 2.8, respectively. Quality management and compliance applications attracted significant interest from participants. Specific applications/proposals included automated electronic Certificate of Analysis (eCOA) acceptance, image processing for quality inspection, and process standardization through AI. The appeal of these applications stems from their potential to inspect all items as opposed to samples, reduce manual inspection errors, accelerate compliance verification, and ensure consistent quality standards across production facilities. However, these potentials are challenged by the regulatory compliance, trust, and reliability issues associated with the AI. On the other hand, this may stem from the fundamental lack of defect data to feed the learning, as commonly documented in the literature. Production planning applications proposed by participants focused on operational efficiency through AI-enabled process selection, resource allocation, bottleneck resolution, and material transportation optimization. These applications could enhance production flexibility and responsiveness by taking into account a greater variety of data, and learn and adapt based on the outcomes. However, participants identified critical obstacles that include data standardization across facilities and the absence of "gold standard" datasets for training AI models. This data challenge proves particularly acute in manufacturing due to proprietary process data and significant variations in equipment and operating conditions.

4.4. Delivery and Return

AI applications for delivery and return get the highest average maturity levels (4.2), the same as for Source. This high assessment may reflect participants' awareness of successful AI deployments in logistics and e-commerce, along with the availability of operational data and well-defined performance metrics in these domains. However, participants identified ongoing challenges, including integrating AI agents with ERP/MES systems, data quality issues, and insufficient training data, particularly for computer vision applications. Logistics optimization applications align with evidence in the literature [3-5] that AI enhances classical vehicle routing algorithms by analyzing a wider range of data, such as historical traffic patterns, delivery success rates, and seasonal variations, to improve route planning. In addition, AI continuously learns from operational experience to adapt routing decisions and dynamically reroutes vehicles in response to real-time traffic congestion, failed deliveries, and new order arrivals. Automated packaging optimization leverages e-commerce data volumes for effective training. These systems select optimal configurations to minimize cost and logistics space. Robotic bin picking combines AI-based computer vision with manipulation to automate material handling, while alternative approaches use AI to augment human workers through error detection and decision support. Return management applications use AI to classify complaints and predict returns. Using LLM and agentic AI, it can read and interpret customer messages, emails, or chat to determine complaint types. The extracted insights could be used for predictive models that estimate the likelihood of product returns, enabling proactive measures such as product redesign and quality checks.

4.5. All SCOR Processes

While the previous sections addressed process-specific applications, AI-enabled data integration and traceability span all processes and are aligned with Dr. Kim’s presentation to potentially use RAG and GraphRAG as a semantic backbone for other AI applications. In that semantic backbone, AI was used to automatically combine and feed data from different systems that had different formats, time scales, and quality levels into the RAG and GraphRAG. However, as Kim mentioned, the resulting integrated data were not always right and hence would have limited use for automation. AI could also consolidate scattered data to reconstruct complete product journeys, identify suppliers, facilities, and routes involved, and detect patterns in problematic pathways. In our extended view, the ultimate goal of these AI applications could be supply chain digital twins - digital replicas of entire supply chain networks that integrate data across all SCOR processes. These systems would enable organizations to simulate different scenarios and test strategic decisions in virtual environments before implementing them in the physical supply chain. A planning decision could be evaluated for its impact on sourcing, manufacturing capacity, delivery logistics, and potential returns. With real-time synchronization capabilities, digital twins could continuously reflect actual supply chain conditions across all processes, allowing organizations to detect emerging issues and proactively plan responses to disruptions. This holistic view represents a significant advancement from process-specific optimization, enabling truly integrated supply chain management.

4.6. Challenges in Realizing AI Applications in SCM

Even though each process in the SCOR model has unique characteristics and operational contexts, the challenges in realizing AI applications are remarkably similar across processes. This convergence suggests that AI challenges stem from issues associated with data management, systems integration, and skills rather than technology selection. Data quality and availability, together with the security concerns from data sharing, are recognized as a significant contributing factor to the success of AI applications in the SCM field. Organizations face inconsistent data quality across systems with varying formats and reliability. Lack of standardization across organizational boundaries compounds this as suppliers, manufacturers, and logistics providers operate incompatible systems (e.g., ERP, MES, WMS, etc.) and precisely integrating data between them is still challenging. Security and privacy concerns further constrain data sharing and, hence, availability. Additionally, other technical barriers during the realisation of AI in SCM are noticed, including explainability of the ML models for domain experts and real-time performance requirements from some critical management processes. Organizational challenges include critical skills shortages in combined AI expertise and supply chain domain knowledge, resistance from managers who prefer experience-based decisions over unexplainable AI, and inter-organizational issues such as data privacy trust and shared benefits. These challenges are interconnected. They reinforce each other: poor data reduces AI performance, which lowers trust, and limits investment in better data systems. Successful implementation requires addressing all these issues together, focusing on both improving data quality, building organizational capabilities, and creating business value across the supply chain.

5. Lessons Learned from Running the Workshop

5.1.1. Time

The workshop was planned for three-and-a-half hours but ended up using the whole four hours available time. Attendees engaged from the start of the workshop with a lot of questions and discussions during the keynote presentations. Keynote presenters also had more materials than the time allocated and faced technical challenges in the remote presentations. While this showed all the parties' excitement about the topic, this resulted in a shorter time available for the brainstorming section. Since the workshop schedule was already thirty minutes overlapped with lunch, the time could not be extended. The brainstorming section was left with one-and-a-half hours instead of the originally planned two hours. The thirty-minute loss took its toll on the stages during the brainstorming section, which required group discussions. Interesting discussions have to be cut short, even with just thirteen participants and the three-idea limit during the proposal stage. We believe that if all thirty participants were to show up, the two allocated hours for the brainstorming section might still feel limited for a lively discussion.

5.1.2. Participation

Keynote presenters already have a good number of ideas for AI applications in supply chains. This was not expected by the organizers. Although the remote presenters expressed desires to participate in the brainstorming section, the parallel discussions in multiple groups would have been too difficult in the hybrid mode. In retrospect, if these were known in advance, a plan could have been made to discuss the presenters' ideas in a single thread with all the participants.

5.1.3. Participants Background

Most workshop participants came from the field of supply chain operational research, with attendance largely composed of academic professors and researchers. Their familiarity with AI and its large-scale implementation was limited. The inclusion of AI and supply chain industry experts in the keynote session helped to provide practical insights that grounded the subsequent brainstorming activities. However, some participants hesitated to propose specific AI applications or challenges, citing insufficient background in AI. A more diverse mix of participants could lead to clearer application ideas and more concrete challenges. To achieve this, each group could be structured to include at least one AI expert and one supply chain management (SCM) industry professional.

5.1.4. The Brainstorming Process

The structured brainstorming process using distinct stages provided a systematic framework for capturing and refining ideas. While it took some time to explain the process at the beginning, participants' feedback was positive about the effectiveness of the process, barring the shorter-than-planned time. They enjoyed the group's discussion and collaboration to clarify and consolidate ideas. The time efficiency could be improved by not explaining the whole process at the beginning. Briefly introducing the overall process at the beginning and only providing details at the start of each stage could have saved some time. Dividing the board into areas corresponding to the SCOR process for classification was not optimal, because some ideas were applicable to more than one process. The idea was to use the areas surrounding and in the middle of the SCOR process boxes to indicate the multiple applicabilities. But it took too long to explain that, and the areas were too small to clearly place the post-it card. A better solution could be to use a label/tag similar to assigning the SCM issue categories. This way, the different areas on the board could be used for each group's work instead. And normalizing and clarifying the ideas could be done in each group first and then across the whole workshop. The digital brainstorming platform enabled real-time collaborative idea capture and edit, facilitating the normalization process through visual organization and digital manipulation of concepts. However, the platform introduced a small learning curve, although the organizers' strategy to station a platform expert in each group was effective. While efforts were taken by the organizers to ensure participants' access to the platform prior to the workshop, time still needed to be budgeted for such an issue. The organizers should have planned to ask the participants as they came into the room about their accessibility to the platform and address the issue during the keynote talks, rather than waiting until the brainstorming section. Overall, while there is always an internet risk and some accessibility and learning curve issues, we believe the digital board was more productive than a physical board and post-it, especially with the data processing after the workshop. On the other hand, preparation to use the physical board also had to be made, just in case.

6. Conclusion and Future Work

By combining the practical use cases from the industrial domain and brainstorming opinions from academic and public/private research participants, the workshop successfully brought together diverse insights from both sides, which explored AI potentials and its challenges across supply chain management. The knowledge gathered from the workshop can enhance a better understanding of AI in this domain and inform future research directions.

AI use cases were presented by four keynote speakers who provided insights from both academic and industrial projects. From an academic point of view, Prof. Kumara's presentation provided essential theoretical foundations by tracing AI's evolution through three waves, helping participants understand where AI is heading. In addition, Prof. Kumara presented AI sustainability challenges, including energy and other resource consumption, environmental impacts, and regulatory constraints associated with responsible AI adoption. These indirect, non-technical challenges raised the necessity for broader societal considerations that are typically secondary from the industrial perspective.

RAG emerged as a critical enabling technology across multiple presentations: Prof. Kumara's projects validated the GraphRAG-agentic AI architecture from a research perspective. Dr. Kim from Google highlighted the usage of RAG/GraphRAG to address data heterogeneity challenges in their operations, and Dr. Strandhagen from SINTEF proposed RAG for shop-floor copilot. This convergence indicates the benefit of AI with RAG to address critical supply chain challenges in documentation analysis, knowledge management, and decision support.

The presentations on industrial AI applications focus on three sectors, which are biopharma, consumer electronics, and shipbuilding. The potentials of AI in these sectors are highlighted in demand forecasting, quality control, logistics optimization, and risk management. However, the presentations also revealed differences in AI maturity levels across industries. The biopharma and shipbuilding industries remain in the early stages of AI adoption, primarily addressing foundational issues such as system heterogeneity, data standardization, and the establishment of interoperable digital infrastructures. In contrast, consumer electronics demonstrated some mature, large-scale pilot or deployment-stage AI systems, including deep learning models for demand forecasting and generative AI applications for customer service automation.

Regardless of their maturity levels, all three sectors considered data challenges as the primary barrier to AI success. Biopharma struggles with foundational issues. Google, despite its advanced AI capabilities like GraphRAG, "reliability" still has its issues. Shipbuilding faces the challenge of coordinating complex digital twin systems across multiple data streams for project management. This pattern reveals that data integration and governance challenges persist across the AI maturity spectrum, simply evolving in complexity as organizations advance.

The brainstorming session generated AI application ideas that align with the keynote themes. Source and Delivery & Return processes received the highest maturity assessments (4.2), likely reflecting participants' awareness of public data availability and existing implementations in these processes. In contrast, Plan (2.8) and Make (2.9) applications received significantly lower maturity ratings and generated fewer specific application proposals. However, these lower assessments should not be interpreted as an indication of less AI adoption potential. Despite these differences in maturity, participants identified similar challenges across all processes, particularly concerning data quality, legacy integration, explainability, and real-time performance.

In terms of future work, it could be worthwhile to repeat the workshop with a larger and better mix of participants as discussed in the lesson-learned section. Alternatively, an online, passive survey may be conducted to get to even broader participants. In these cases, better entries and descriptions of ideas and challenges may be produced. Taking the AI application ideas from this report and conducting a wider online survey on the maturity or a detailed literature review could be worthwhile to validate the maturity obtained in this workshop as well.

Beyond refinements of the workshop, the factors that enable organizations to progress from low to high AI maturity levels within specific supply chain processes could be investigated. The underlying mechanisms driving these differences remain underexplored. Tracking organizations over time as they implement AI could reveal what capabilities, data systems, and management practices help them succeed.

The workshop identified major challenges around data sharing, security, privacy and standards. These issues need more research attention. Future studies could look at how organizations can work together more effectively when using AI across supply chains. This is especially important for Planning and Sourcing, as the workshop showed that good AI technology alone is not enough without solving these collaboration problems.

Ultimately, this workshop demonstrates that realizing AI's potential in supply chain management requires more than technological innovation. It demands a holistic approach that integrates robust data infrastructure, appropriate architectural patterns like RAG, cross-organizational collaboration frameworks, and careful consideration of sustainability and societal impacts. The path forward lies not in isolated technical solutions, but in coordinated advancement across these interconnected dimensions.

7. Remarks

In closing, the application of AI is recognized as potential to enhance the SC's performance in multiple dimensions. Despite the difference in perspectives, both industrial and academic AI projects converge at several common points regarding technology selection and its implementation challenges. Readiness of these AI projects is varied depending on sectors and techniques. While industrial applications pay attention to how to implement a successful AI project, the academic view also raises awareness of resource consumption and its negative impacts on our environment and society.

The collected information from the brainstorming section provides more extensive and specific AI applications. The classification of AI applications and challenges based on SCOR processes provides a standardized view across industries. They should provide a common ground for future research and comparison of AI impacts.

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