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Generative AI for Unified Bill of Materials: Connecting Engineering, Manufacturing, Service and Sales

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ABSTRACT: In general, production products are usually based on numerous Bills of Materials (BOMs) such as engineering BOMs to design, manufacturing BOMs to produce, service BOMs to service, and sales/customer BOMs to configure. Although these BOMs are optimized according to various life cycle phases, their segregation is likely to cause fragmentation of data management, which causes version discrepancies, manual redundancy, and data quality problems. These issues are a great impediment to efficient product development and after sales.

This paper provides a framework of Generative AI-based unified Bill of Materials (BOM) management to overcome these constraints. Using Generative AI and machine-learning algorithms, the suggested framework is able to automatically extract the BOM data in unstructured sources and harmonize several perspectives of BOM into a single representation. As an example, an AI-based system can decipher engineering drawings and technical documentation in the format of PDFs to create structured BOMs, which saves a ton of manual work and saves time on processing.

The suggested strategy will allow a smooth process of co-ordinating the engineering, manufacturing, service, and sales processes, which will enhance cross-functional coordination and real-time decision-making. The paper explains the ways in which Generative AI implementation in BOM management improves the accuracy of data, shortens the time of product development, and minimizes operational losses. Additionally, it outlines the opportunities of the suggested framework to enhance the integration of the enterprise systems and competitiveness of the organization according to the changing demands of the market.

KEYWORDS: Generative AI**,** Bill of Materials (BOM)**,** Data automation**,** Lifecycle management**,** Machine learning**,** Systems integration**,** Product development efficiency

I. INTRODUCTION

The Bill of Materials (BOM) concept is very important in the current manufacturing and product development. BOM is a detailed list of raw materials and components, as well as sub-assemblies and other resources needed to make a complete product. Nevertheless, the effective management of BOM becomes more difficult as products become increasingly complex and are needed to address the requirements of the different stakeholders, which include the engineering, manufacturing, service, and sales teams. Historically, BOMs are kept per stage of the product lifecycle, e.g. the engineering BOM (design), the manufacturing BOM (production), the service BOM (maintenance), and the sales BOM (configuration). Although these BOMs have different purposes, they tend to work independently and hence result in inconsistencies, errors, and inefficiencies [1].

The issue of having various BOMs in different departments is further complicated by the complexity of the modern day product that commonly incorporates complex systems and also undergoes rapid changes throughout its life cycle. This division may result in version differences, whereby various departments will be using old or incompatible BOM data, and may result in the duplication of work, which adds to the risk of human error. Problems in data quality also lag down product development, after sales services and inter-team cooperation. These issues not only make the process less efficient, but may also cause a decrease in the quality of the product and its delivery to the market [2] [3].

The emergence of new technologies, especially the Generative AI (GenAI) and machine learning (ML) can provide a radical solution to these old issues in BOM management. Generative AI is a subdivision of artificial intelligence that involves the use of algorithms to generate data structures or models that can generate new content. With the use of machine learning, GenAI can offer automated data extraction, fill in gaps between data using disparate BOMs, and align various perspectives of BOMs across departments. As an illustration, AI-based tools could fastly process and transform unstructured data in the form of engineering drawings or technical documents to structured BOM formats, and save a lot of time on the manual preparation and enhance the data accuracy.

Automation and streamlining of the BOM management process by GenAI can resolve most of the problems of modern manufacturers. The AI technologies would be able to support real-time decision-making by uniting the engineering, manufacturing, service, and sales BOMs and make sure that all departments are dealing with the current and correct information. This integrated way of doing things eradicates manual operations, human mistakes and shortens the time of products to the market besides enhancing the overall quality of the product and after sales services.

The main goal of this research paper is to discuss how Generative AI can be applied to optimize the BOM over the whole product lifecycle. The current paper dwells upon the potential of integrating AI-powered tools into enterprise systems to design a single BOM, which integrates engineering, manufacturing, service, and sales operations. The paper will also examine the advantages of such integration which are better data consistency, less operational inefficiencies and faster product development. This paper will show that AI-based BOM management can result in better collaboration between departments, improved product quality, and more efficient after-sales services using case studies and examples.

The subsequent parts of this paper will thoroughly examine the situation with BOM management comprising the present condition of silo-ed systems and the ways in which Generative AI can be used to combat them. The technologies that underpin Generative AI, machine learning, and natural language processing will also be analyzed in the paper in terms of how they are utilized in BOM management. Also, the paper will address the implications of AI integration on the business process at a larger scale in terms of how it can be used to revolutionize the process of manufacturing and enhance business competitiveness on the whole.

This paper will be useful in expanding the body of research concerning the use of AI in industrial contexts and offer assistance to companies that wish to advance their product development. The possibility of AI to bridge the gaps between divergent BOMs and offer real-time and accurate data to all the stakeholders is a tremendous step forward in product lifecycle management evolution. The broader implications of AI on the manufacturing business, specifically in the areas of efficiency, innovativeness, and long-term competitiveness through a fast evolving marketplace, are also expected to be pointed out in this research.

II. RELATED WORK

Within the sphere of software risk management, a number of studies have led to the comprehension and enhancement of software risk management processes, particularly in regard to the global software development. Alqahtani, Banitaan, and Banitaan [1] conducted a systematic literature review of Software risk management practices in the global software development settings. The paper has underscored the problems in managing risks especially in distributed and cross-cultural development teams and the role of effective communication and process integration in reducing the risks. It is a foundational work in the understanding of the intricacies of managing the software development risks, particularly with multi-disciplinary teams and technologies, which is a concern with AI-driven Bill of Materials (BOM) systems.

Recently, the attention has been drawn to the integrity and accountability of data in AI and machine learning models. Barclay et al. [2] suggested that verifiable credentials should be used to assure and scrutinize shared data and machine learning models. Their work provides some understanding of how verifiable credentials can be employed to improve the traceability, which can be incorporated into the AI-based BOM systems to guarantee the transparency and accountability of managing and processing product data. Moreover, Barclay, Preece, Taylor, and Verma [3] investigated the application of the BOM models in enhancing the traceability in the data ecosystem, and suggested using the standardized data models to overcome the barriers that exist between different data sources, including engineering, manufacturing, and service, which is aligned with the objective of consolidating BOM data across the different departments.

Benedetti et al. [4] studied the effects of Generation Software Bill of Materials (SBOM) in Python vulnerability analysis. Their paper exemplifies the use of automated tools to create and maintain SBOMs to analyze software vulnerabilities as a new way of creating BOMs that are capable of incorporating vulnerability information to make

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better decisions. The concept of application of AI to automate and improve the BOM creation has been supported in this paper, especially with regard to security and quality evaluation.

Bennet et al. [5] studied the application of AI-based Bill of Materials (AI BOM) using SPDX 3.0 standard. This paper highlights why the issue of standards is vital to maintaining a consistent and interoperable BOM in different teams and technologies. With the use of AI-driven BOMs based on the standard of SPDX 3.0, BOMs generation, reconciliation, and tracking may be significantly simplified, allowing easy integration of engineering, manufacturing, service, and sales functions.

Blind and Boehm [6] have discussed the significance of open-source software in standard-setting, and its connection to software governance in which they talked about the open-source software role in industry standard-setting. This is of immense importance when taking into consideration integration of open-source tools in the AI-based BOM management where the tool should be compatible and widely adopted to BOMs generated by AI in the industry.

The Center for Devices and Radiological Health addresses the topic of cybersecurity concerns of software systems, especially in the field of medical equipment [7]. Their analysis of premarket submissions and quality systems is of great use to understand how BOMs should additionally comply with cybersecurity requirements, particularly when sensitive information or critical systems are involved.

Additional attempts to match cybersecurity with SBOM management can be located in the report of the European Commission [8], which highlights the necessity to employ open-source standards in the context of ensuring security and traceability of software components. The introduction of AI to such operations would further streamline the process of policing and keeping up security within the BOM, particularly within the healthcare sector or critical infrastructure.

Under the Secure AI Framework (SAIF), the Coalition for Secure AI [9] has proposed a risk assessment tool, which may be significant in securing AI models that are part of BOM management. The tool is in response to the growing demand of securing AI systems in industries to supplement work on integrating and simplifying BOMs across departments.

The purpose of the SPDX standard and its application in the AI systems were also examined by the SPDX contributors [10]. Their paper emphasizes the value of standard documentation to handle software components and it can be applied to the management of AI-driven BOMs to promote consistency and security in data sharing.

The following outline of the OpenChain project by Coughlan [11] focuses on establishing confidence in the open-source supply chains. The initiative is applicable to AI-driven BOMs because it highlights the importance of transparent and verifiable sources of data, which is critical in ensuring the integrity of AI-generated BOM data.

Cybersecurity and Infrastructure Security Agency (CISA) [12][13] has come up with instructions on the development and dissemination of SBOMs in response to the increasing need of secure and efficient management of SBOMs. These rules are useful suggestions that organizations that intend to implement SBOMs in their AI systems should follow in making sure that they are secured properly and can be easily shared by the various teams and stakeholders.

Combined, these studies result in a strong background of the issues and possibilities of AI-based BOM systems. They emphasize the significance of standardization, traceability, security, and transparency, all of which are important features that qualify the successful management of BOMs in the functions of engineering, manufacturing, service, and sales.

Table 1: **Comparative Summary of Related Work on Software Risk, SBOM, and AI-based BOM Systems**

Ref.	Authors	Focus Area	Key Contribution	Relevance to AI-based BOM
[1]	Alqahtani et al.	Software Risk Management	Identified risk challenges in global and distributed development	Informs risk handling in AI-driven BOM across distributed teams
[2]	Barclay et al.	Data Integrity	Proposed verifiable credentials for trusted data sharing	Enhances traceability and accountability in AI-based BOM

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[3]	Barclay et al.	BOM Traceability	Standardized BOM models for cross-domain integration	Supports unified BOM across engineering and services
[4]	Benedetti et al.	SBOM Automation	Automated SBOM generation for vulnerability analysis	Enables AI-assisted BOM creation with security insights
[5]	Bennet et al.	AI BOM Standards	Applied SPDX 3.0 for AI-based BOM interoperability	Ensures consistency and lifecycle BOM management
[6]	Blind & Boehm	Open-Source Governance	Linked open-source software to standard-setting	Supports adoption of open standards in AI BOM tools
[7]	CDRH	Cybersecurity Compliance	Defined cybersecurity requirements for software systems	Guides secure BOM design in regulated domains
[8]	European Commission	SBOM & Security	Advocated open standards for secure traceability	Aligns AI-based BOM with regulatory expectations
[9]	Coalition for Secure AI	AI Risk Assessment	Introduced SAIF risk evaluation framework	Addresses AI model risks within BOM systems
[10]	SPDX Contributors	Documentation Standards	Established standardized software component records	Improves interoperability of AI-driven BOMs
[11]	Coughlan	OpenChain	Ensured trust in open-source supply chains	Strengthens reliability of AI-generated BOM data
[12] [13]	CISA	SBOM Guidelines	Issued SBOM creation and sharing best practices	Provides operational guidance for AI-enabled SBOMs

III. CURRENT CHALLENGES IN BILL OF MATERIALS (BOM) MANAGEMENT

Efficient management of Bills of Materials (BOMs) has been a fundamental issue in product development particularly in products that are increasing in complexity and also those products that are needed to address the needs of various departments including engineering, manufacturing, service and sales. Although BOMs are so vital, existing systems tend to find it difficult to synchronize the multiple BOMs that are being kept at different phases of the lifecycle, which then causes serious inefficiency, mistakes, as well as delays.

Fragmentation of data is one of the main problems in the management of a BOM. Traditionally, manufacturing facilities use different departments that maintain separate BOMs that fit their requirements. The engineering teams produce engineering BOMs that define the design specifications of a product and the manufacturing teams produce manufacturing BOMs used in the manufacturing process as well as the service departments produce service BOMs used in maintenance and repair. The sales teams also use customer BOMs to offer products based on specifications by the customers. Although such BOMs are used to achieve different objectives, they are usually loosely coupled with each other that leads to version mismatches and the need to continuously update systems. Lack of a standardized BOM causes problems related to the need to guarantee that all stakeholders are dealing with the latest and best information.

Manual duplication and data entry is also another major challenge. Since most organizations continue to operate under their legacy systems or using manual system to manage their BOMs, there are chances that employees are repeating themselves when passing information across departments. To illustrate, an engineering BOM can be required to be reformatted to a manufacturing BOM, and thus same information have to be entered in to more than one system. This will enhance chances of human mistake like errors in part numbers, description or quantity which can result to delays in production and service.

Moreover, the data silos are due to the absence of integration between BOMs across departments. Each department uses its own version of the BOM and makes discrepancies that may affect products development, production schedule and after sales service. That is the reason why these data silos complicate teamwork. An example would be that in case an engineering design change is implemented, the manufacturing and service departments would not be aware of it immediately and thus they might make a mistake in production or maintenance. This kind of non-synergizing does not promote effective decision making and slows down the whole lifecycle of the product, which is the design process to production and service.

The problem of data quality also poses a significant threat of the conventional BOM management. When data is transferred or updated by hand when moving between systems, it is highly prone to data degradation. The absence or

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wrong data, including obsolete part specifications, or incomplete bill of materials records can lead to delays in production, higher costs, and low quality products. Ineffective supply chain and misallocation of resources as well as erroneous forecasting may also occur due to inaccurate data. Organizations are always facing a challenge in ensuring the accuracy of the BOM data especially when it comes to various departments.

Also, modern products are becoming more and more complex, making these challenges even more difficult. The BOMs needed to handle such products continue to increase exponentially in size and complexity as the products themselves become more complex, containing multiple components, software and systems. These complex BOMs have to be managed with effective tools to work with large data sets and to ensure accuracy throughout the lifecycle of the product. Conventional processes tend to be poorly suited to manage this complexity, and a company can have difficulties incorporating new product modifications or designs in an existing BOM system.

Not only these challenges cripple the efficiency of operations but also affect the bottom line. These mistakes, time wastage, and lack of efficiency due to siloed and fragmented BOMs can result in escalation in costs and lost market opportunities as well as customer satisfaction. Organizations that do not handle such issues are likely to lag other organizations that are well-prepared to handle complex product information on-the-fly.

IV. FRAMEWORK FOR GENERATIVE AI IN UNIFIED BILL OF MATERIALS MANAGEMENT

The challenges produced by the fragmentation of Bill of Materials (BOMs) among various functions in the product development-engineering, manufacturing, service, and sales functions are quite demanding and affect the efficiency of the operations, accuracy of data, and collaboration. Conventional systems and processes tend to lead to siloed strategies with each department having a variant of the BOM that is not integrated smoothly. The resulting effect of this haphazard mechanism is data inconsistency, manual redundancy, and product development and after sales delay. Providing a solution that is transformative to this issue, Generative AI (GenAI) can be deployed to automate and standardize all departments in terms of BOM management. This framework suggests a systematic solution to implement GenAI into the BOM management system to overcome the challenges and to disclose the maximum potential of BOM optimization.

1 Design Requirements for Generative AI–Enabled Unified BOM Framework

Authoritative source control: The proposed framework must clearly define and preserve authoritative systems of record for BOM attributes across the enterprise. For example, product structures shall remain governed by PLM systems, while item masters and costing data shall be maintained within ERP systems. Generative AI components must not modify authoritative data fields without explicit approval, ensuring data ownership and consistency.

Traceability and auditability: All AI-driven BOM extraction, reconciliation, and alignment decisions must be fully traceable and auditable. Each decision should be version-controlled and linked to supporting evidence such as engineering drawings, document revisions, change notices, or supplier updates. This requirement ensures transparency, regulatory compliance, and trust in AI-assisted outcomes.

Configuration and effectivity management: The framework must support complex configuration rules, including product variants, serial and lot effectivity, plant-specific alternatives, and service supersessions. Generative AI models should correctly interpret and propagate effectivity constraints across engineering, manufacturing, service, and sales BOM views.

Governance and human-in-the-loop control: To maintain compliance with established change management practices, the framework must incorporate human-in-the-loop workflows. AI-generated or reconciled BOM changes should be subject to review and approval processes aligned with engineering change control, manufacturing release, and quality governance policies.

Interoperability and standards compliance: The framework must support interoperability across enterprise systems through standardized interfaces and integration patterns. Compliance with widely adopted standards—such as ISA-95 for enterprise–manufacturing integration and STEP AP242 or QIF for product and quality data exchange—is required to enable scalable and vendor-neutral deployment.

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2. Reference Architecture

Generative AI is a term used to describe a range of algorithms and machine learning systems that can be used to produce new data or structure with the help of existing data. GenAI is applicable in the context of BOM management to automate different processes involved in production such as BOM creation, maintenance, and interdepartmental reconciliation. GenAI can be used to process unstructured data (e.g., engineering drawings or product specifications or technical documents) and transform it into structured data formats that can be used in other systems by utilizing methods like Natural Language Processing (NLP) and machine learning.

GenAI integration in the BOM management systems will facilitate automatic data extraction, unhindered data transfer, and real-time decision-making. It assists in developing an integrated BOM to close the engineering, manufacturing, service and sales functions. GenAI technologies are also able to make data consistent and accurate so that it can minimize the number of human mistakes and enhance cooperation among various teams responsible in the product lifecycle.

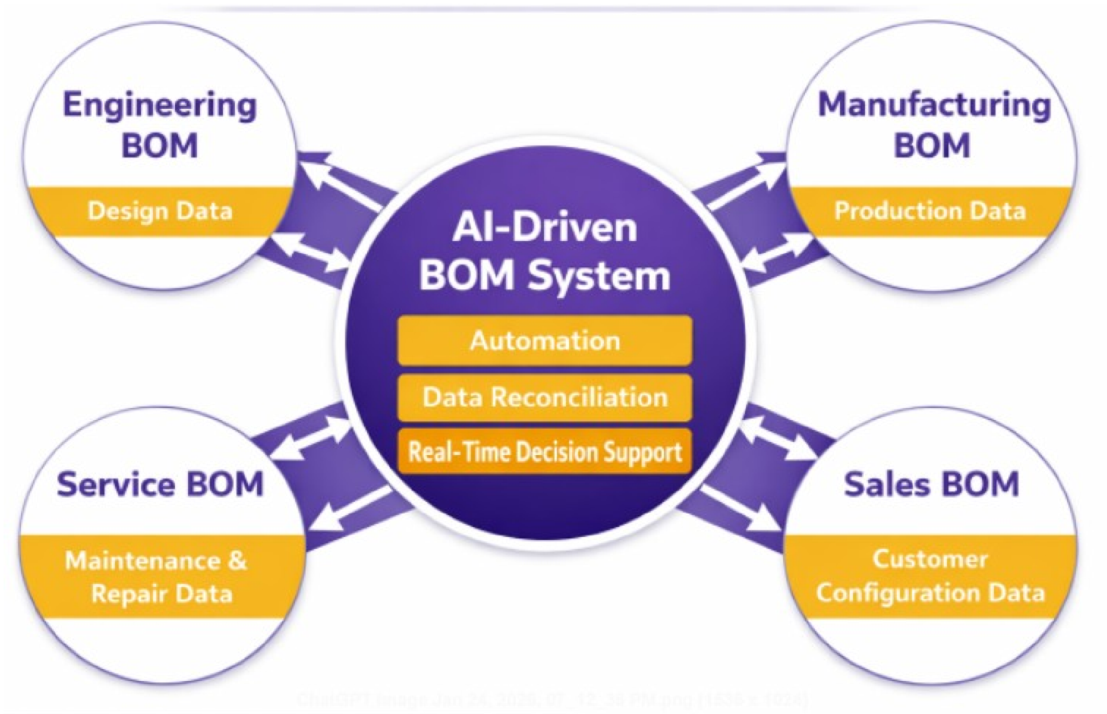

Figure 1. Conceptual Overview of AI-Driven BOM Integration across Engineering, Manufacturing, Service, and Sales.

The illustrated framework represents a **Generative AI–driven unified Bill of Materials (BOM) system** that integrates engineering, manufacturing, service, and sales BOM views through a layered architecture.

(L1) Data sources: At the foundation, the framework integrates heterogeneous enterprise data sources. These include PLM systems providing Engineering BOMs (EBOMs), CAD metadata, and design revisions; ERP systems managing item masters, routings, and costing information; MES systems capturing work instructions and as-built manufacturing records; service and CRM systems containing maintenance histories, field failures, and spare-part supersessions; and sales systems defining customer-specific configuration rules. These sources correspond to the Engineering, Manufacturing, Service, and Sales BOMs shown at the periphery of the diagram.

(L2) Ingestion and evidence capture: Data from these systems is ingested through standardized connectors capable of handling both structured records and unstructured artefacts. Engineering drawings, PDFs, and engineering change orders (ECOs) are processed and stored as immutable evidence objects in a document repository. Each extracted BOM element maintains a reference to its original source, enabling traceability and auditability.

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(L3) Semantic normalisation: A semantic layer based on a domain ontology and knowledge graph harmonizes identifiers, units of measure, part attributes, and relationships across BOM views. This layer aligns all inputs to a canonical schema, grounded in established standards such as ISO 10303 STEP for product structure representation and ISA-95 for enterprise–manufacturing integration.

(L4) Reconciliation and rules: The core intelligence of the system performs BOM reconciliation using a combination of deterministic and probabilistic techniques. Deterministic rules enforce configuration constraints, effectivity, alternates, equivalence, and plant-specific substitutions, while probabilistic entity-resolution methods identify likely matches and conflicts between BOM elements originating from different lifecycle stages.

(L5) Generative AI copilot and workflow: At the top layer, a Generative AI–based copilot supports users by providing evidence-linked explanations, proposing BOM alignments or change actions, and assisting in conflict resolution. All AI-generated recommendations are routed through governed, human-in-the-loop approval workflows aligned with engineering change control and manufacturing release processes. Once approved, validated updates are propagated back to the authoritative source systems.

3. Data Integration and Reconciliation: Connecting Siloed Systems

Enabling data to be integrated and reconciled across siloed systems is one of the main tasks that GenAI has in BOM management. There are many variations of BOMs, such as the engineering, manufacturing, service and sales teams, each of which is optimized to match the needs of the team. GenAI can be used to automate the process of reconciling these different BOM images and make sure that all stakeholders operate on the same up-to-date data.

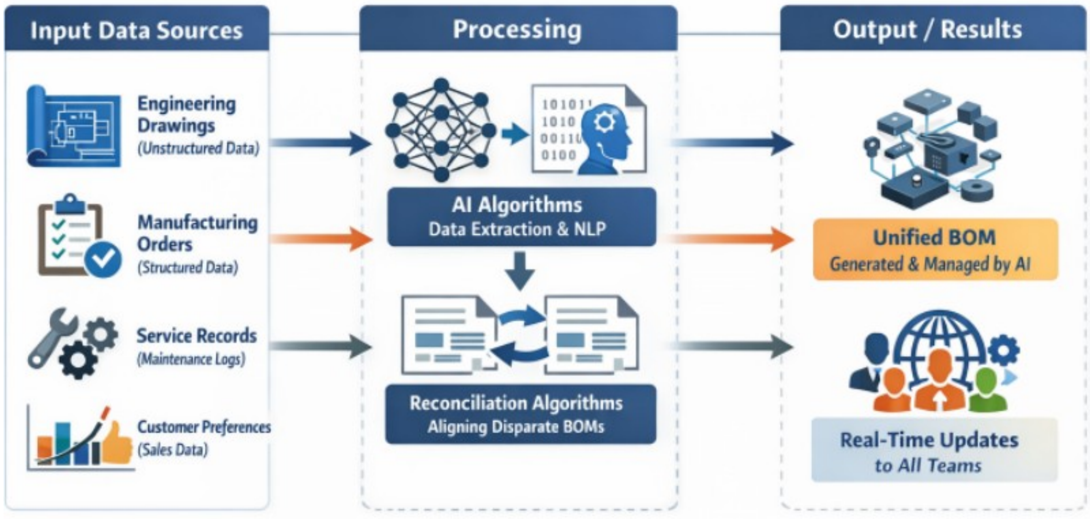

Figure 2. Data Flow within the AI-Driven BOM System.

The figure illustrates an end-to-end workflow for Generative AI–enabled unified BOM management, progressing from heterogeneous data ingestion to enterprise-wide BOM publication.

Step A – Extract:- LLM-assisted parsing is applied to structured and unstructured inputs, such as engineering drawings, manufacturing orders, service records, and sales configuration data. Item candidates, quantities, units of measure, and contextual notes are extracted, with source references captured and stored as evidence.

Step B – Normalise: Extracted entities are mapped to canonical identifiers, including internal item numbers and manufacturer part numbers. Units, naming conventions, and attribute formats are normalized to ensure consistency across BOM views.

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Step C – Match: Entity resolution is performed across enterprise systems using a hybrid approach. Deterministic keys (e.g., part numbers, revisions) are combined with similarity-based features (e.g., textual descriptions and attributes) to identify equivalent or related items.

Step D – Reconcile: Conflicts such as missing alternates, mismatched effectivity, or incompatible revisions are detected. The system generates candidate resolutions and alignment proposals for review.

Step E – Approve and publish: Proposed changes are routed through engineering and manufacturing change-control workflows. Upon approval, reconciled BOMs are published as a unified BOM and propagated in real time to downstream functions, ensuring consistent visibility across teams.

All steps are described in detail as follows:

3.1. Data Extraction from Unstructured Sources

In the traditional systems, unstructured data like PDF drawings, technical specifications, or emails, may frequently require manual processing to make changes to BOMs. GenAI would be able to automatize this process, taking out pertinent information in these unstructured sources. As an example, engineering drawings in PDF format can be analyzed by GenAI-related tools, and the parts and components will be identified and a structured BOM will be prepared in several seconds. This automation does not only save time, but also minimizes human error so that the BOM represents the most correct and up to date data.

3.2. Reconciliation of Disparate BOM Views

The departments can develop and keep their own copy of the BOM with the department-specific requirements. To give an adequate illustration, the engineering BOM can consist of part numbers, specifications and design data and on the other hand, the manufacturing BOM is concerned with assembly steps and production. Service BOMs consist of maintenance parts, sales BOMs dwell on customer specific configurations. GenAI is able to combine these different BOM views into a unified and real-time data model in that any changes in any department will automatically propagate to the other departments. This can remove the manual reconciliation and version control process, and simplify communication and minimize mistakes.

4. Real-time Decision Support: Enhancing Collaboration

The other important point of GenAI application in the BOM management is the fact that it supports real-time decisions. Conventional systems of BOM tend to be manual in updating and sharing of BOM, thus giving rise to delays and miscommunication. GenAI can provide predictive analytics and decision-making, which will allow faster and data-driven decision-making.

4.1. Automated Updates and Notifications

With a cohesive BOM system, which relies on GenAI, any modifications in a single department, i.e. engineering or manufacturing, are automatically transmitted to the rest of the departments. You can take an example of an engineer making a shift in the part specifications or modifying the design, the updated BOM is immediately made accessible to the manufacturing, service and sales team. Real-time notification and alerts can be created to update other concerned parties about changes. This real-time data flow will help keep every team on track and with the most current data of the BOM on the current version, decision-making is faster, and errors are costly to make.

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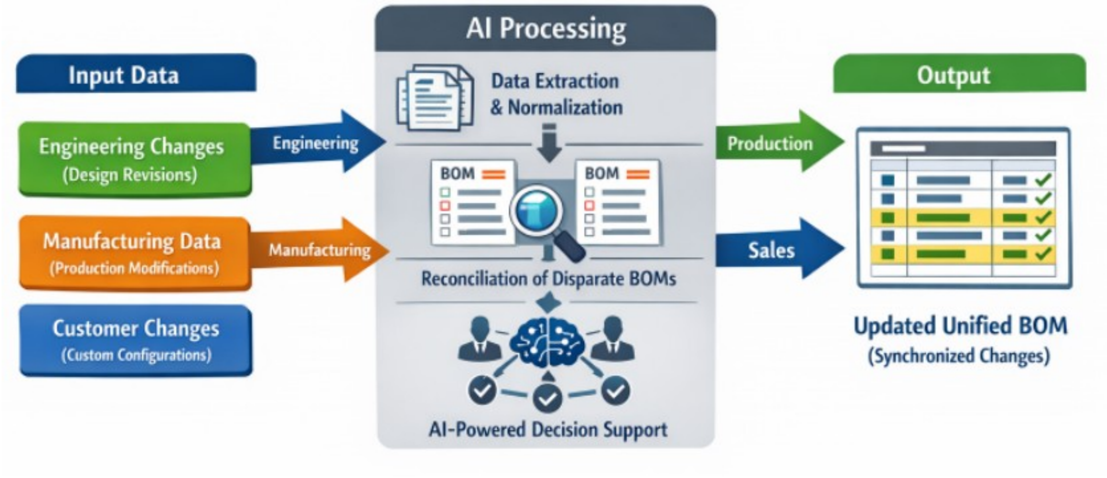

Figure 3. AI-Based BOM Update and Synchronization Process

Figure 3 highlights how engineering, manufacturing, and customer-driven changes are processed through an AI-enabled pipeline to produce an updated unified Bill of Materials (BOM). Design revisions from engineering, production modifications from manufacturing, and configuration changes originating from customers are ingested as input data streams. These inputs are subjected to AI-based data extraction and normalization, followed by reconciliation of disparate BOM views. An AI-powered decision-support layer evaluates the impacts of changes, resolves inconsistencies, and ensures alignment across lifecycle stages. The outcome is an updated unified BOM with synchronized changes, which is then made available to production, sales, and other downstream stakeholders, enabling consistent and timely decision-making across the enterprise.

4.2. Predictive Analytics for Product Development and After-Sales Support

GenAI also has an opportunity to use the historic data and predictive analytics to streamline the product development process. As an example, using GenAI, it is possible to analyse previous BOM data and determine the trends, possible bottlenecks, and improvement opportunities. Within the framework of after-sales services, GenAI may forecast the most frequent repairs or components to need specific maintenance and, therefore, service teams will be able to replenish inventory proactively and increase customer satisfaction.

5. Enhancing Data Quality and Accuracy

The quality and accuracy of data is very crucial in BOM management. Wrong or old data may create delays in production, quality complications and hiked costs. GenAI assists in improving the quality of data because it automatizes data entry to minimize the necessity of manual data entry and ensures that the data remains correct and consistent throughout the company.

5.1. Error Reduction through Automation

Mistakes in human entry of data occur regularly where BOMs are updated by hand. GenAI gets rid of this issue through automation of data extraction and entry where any information that is entered in the BOM system is accurate. GenAI eliminates the chance of errors concerning part numbers, quantities, or specifications by minimizing the amount of manual intervention. The result is a precision in product development, ease of production and fewer post sales service problems.

5.2. Data Validation and Consistency

GenAI is also capable of data verification on the input or output side, verifying that there are no inconsistencies or irregularities in the data. As an example, when a part number is changed in the engineering BOM but not in the manufacturing or service BOMs, GenAI will be able to recognize the inconsistency and trigger the corresponding departments to synchronize their records. This guarantees that the same BOMs are used and the errors are detected and improved in real-time enhancing the general quality of data.

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6. AI-Driven BOM Optimization: Improving Product Development Speed

Lack of efficiency in BOM management normally slows down the product development cycles. Manual updating and reconciliation of BOMs among departments is time consuming and usually results in loss of time on production timelines. The product development process can be greatly accelerated with the help of GenAI that will automatic the whole BOM lifecycle, including both creation and maintenance.

6.1. Accelerating Time-to-Market

GenAI can shorten the amount of time invested in the daily operations of generating, updating, and reconciling BOMs because automation will help the teams to concentrate on more valuable processes. As an illustration, instead of converting engineering drawings manually into structured BOM, GenAI can be used to generate the BOM in only a few seconds. This will decrease the time required in manual efforts to introduce a new product to the market hence a company is able to remain competitive within the fast-paced markets.

6.2. Optimizing Product Configurations

GenAI is also capable of optimizing product specifications based on customer needs and past information. AI applications can be used by sales teams to create customer-specific BOMs within a very short time according to the predetermined parameters, like customers product preferences or configurations. This optimization saves time that would be wasted on manual customization and has the end product to satisfy the customer.

7. Scalability and Flexibility in Complex Manufacturing Environments

The increase of product lines also leads to the more complicated BOM management needs because the solutions should be more scalable and flexible. GenAI provides the scalability needed to support large datasets of the BOM and the ability to support various product designs and production cycles.

7.1. Handling Complex Product Variations

Today manufacturers can create numerous versions of the same product and each of them will need different BOMs. GenAI enables handling of different product variations under the single, unified BOM system, enabling companies to simply change between the various configuration and modify BOMs to various product models. This scalability also allows the BOM system to survive to the future product lines, which may be simple variants or very complex ones.

7.2. Adapting to Changes in the Supply Chain

Alterations in the supply network, like the shortage of parts or the alteration of suppliers, also tend to necessitate rapid BOM modification. GenAI will be able to modify BOM data promptly when there are changes in the supply chain and will make sure that production schedules are up to date and that any challenges are handled before they can disrupt the production process.

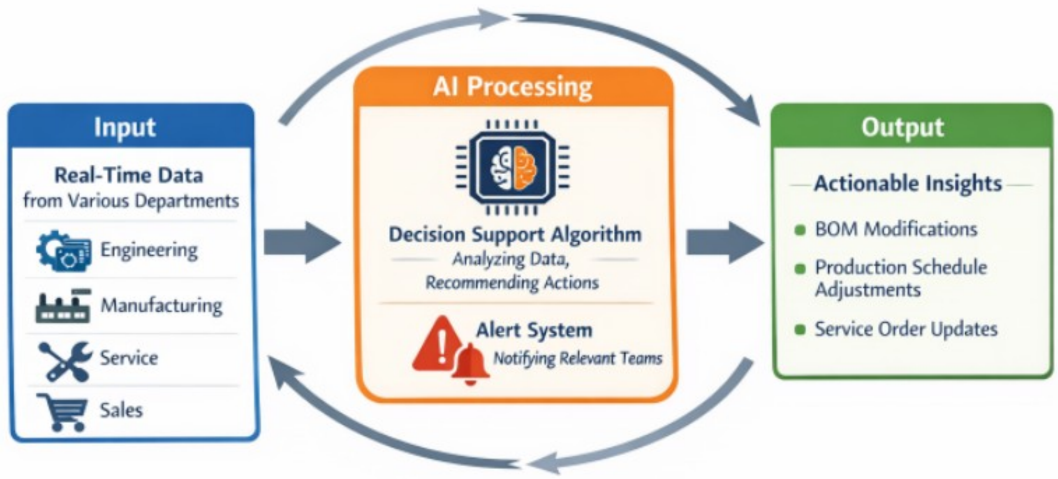

Figure 4: Workflow for Real-Time Decision Support using AI-Driven BOM

V. EVALUATION OF THE PROPOSED FRAMEWORK

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The planned framework of implementation of Generative AI (GenAI) into bill of materials (BOM) management would be a promising approach to the problem of fragmentation, inefficiency, and data quality problems that are common in conventional BOM management systems. Using the features of GenAI to automate the process of extracting data, reconcile the differences between BOM views, and deliver real-time decision support, the framework suggests a considerable change to a coherent, trimmed BOM system. But there is a need to critically evaluate the possible advantages, constraints and difficulties of applying this framework to real life situations.

1. Strengths of the Proposed Framework

1.1. Enhanced Data Integration and Collaboration

The ability to bring siloed data together in various departments, namely, engineering, manufacturing, service and sales, is one of the strongest strengths of the suggested framework. The BOM has been traditionally maintained in each department with the result that there will be inconsistencies, errors, and delays. It is the characteristic of the framework to align these various BOM views to a consistent, real-time piece of information providing an assurance that all the stakeholders are on the same page of available and correct information. This integration helps to ensure improved communications and coordination without necessarily having to manually update and maintain a version control, which tends to cause human mistakes.

1.2. Real-time Decision Support

Another high potential of this framework is the capability of GenAI to give real-time decision support. Traditional systems have features whereby changes done in a department that include engineering are not usually extended across the rest of the departments hence are prone to misalignment and production delays. GenAI also provides access to the most up-to-date and accurate data to all departments because it automates the spread of changes across all BOM views thus helping to make quick and better decisions. This is especially useful in dynamic manufacturing settings where quick response to change and prompt modification is very important in ensuring that operations remain efficient.

1.3. Improved Data Quality and Accuracy

The quality of data used in the traditional BOM system is a major concern since mistakes in the part numbers, description and quantity may lead to expensive errors. The automated data mining and validation systems of GenAI greatly minimize the possibility of human error. GenAI removes the need to enter data manually, so the accuracy of the data is increased as unstructured sources of data, including engineering drawings, are extracted and transferred into structured formats. Also, the fact that the system is capable of validating and cross-checking information between various BOMs increases the overall data consistency that is paramount to the integrity of the product development and production processes.

1.4. Accelerated Product Development

The BOM can be created, updated and reconciled automatically and hence may greatly accelerate product development cycles. With the conventional systems, updating and verifying of BOMs within the various departments can take days or even weeks. GenAI can ensure that it will take less time to react to new products in the market by automating these tasks and providing faster time to market. This is most beneficial in the industry where one of the competitive advantages would be the speed of product development.

2. Potential Limitations and Challenges

2.1. Implementation Complexity

The difficulty of introducing GenAI in the current systems of BOM management is one of the significant issues of the proposed framework implementation. The use of legacy systems is still used in many organizations, and it might not be suitable with the developed AI technologies needed in this structure. The process of the integration can be accompanied by the major changes to be made to the current IT infrastructure, which can be rather costly and demand a considerable amount of time to be implemented. Also, implementing an AI-based system of BOM management can be met with resistance among the staff who will be used to the manual processes.

2.2. Data Privacy and Security Concerns

Like any AI-driven solution, data privacy and security are the essential factors. GenAI is based on the access and processing of vast data regarding sensitive products, such as engineering designs, part specifications and manufacturing processes. It is important to provide the security of this data against any unauthorized access, breaches, or misuse. To protect their AI systems, organizations have to invest in a high-quality level of cybersecurity that may introduce new costs and complexity to the implementation process.

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2.3. Dependence on High-Quality Training Data
The quality of data used in training the AI model is very critical to its performance. GenAI models need large and high quality datasets in order to produce accurate and reliable output. The GenAI models may be hard to train in industries where the BOM data is incomplete or inconsistent. In case the training information does not cover the entire array of product designs or manufacturing operations, the AI model can produce false results, which can cause additional errors in the BOM system.

2.4. Scalability Issues in Complex Environments
Although the framework suggests scalability to manage complicated products and a variety of product models, a system of this scale may be difficult to implement in the large-scale production setting. The more the product lines are diversified, the more complicated the management and updating of the BOMs becomes. The AI-based BOM system will need to have its AI models and supporting infrastructure updated constantly to support a large number of product variants and configurations. This may lead to further maintenance and operating expenses.

The model of incorporating Generative AI in the management of BOM is a potential remedy to the problems of data fragmentation, manual copying, and inefficiencies that have dogged most organizations currently. The framework would also enhance the collaboration, data accuracy, and accelerate product development by automating the data extraction process, reconciling different BOMs views, and provide real-time decision support. Nevertheless, such obstacles like the complexity of the integration, data security, and necessity of high-quality training data will have to be surmounted to make this framework work successfully.
The advantages of the GenAI in the management of BOM in the long run such as efficiency, cost reduction and speed of market turnover may present a massive competitive edge to businesses. With the ongoing progress in AI technology, the introduction of GenAI into the BOM management systems will be the turning point of the manufacturing and product creation in the future.

VI. FUTURE OPPORTUNITIES

The possibility of Generative AI (GenAI) integration with the bill of materials (BOM) management is highly promising in the future due to the potential of transforming the product life cycle management across industries. With the development of AI technologies, their use in manufacturing and product development as well as in the service will grow, providing new opportunities of automation, optimization, and data-driven decision-making. This part examines how AI-based BOM management can develop in the future and where it can be improved.

1. Expansion to End-to-End Product Lifecycle Management
At the present time, the suggested structure is mainly concerned with the issues of BOM management in the engineering, manufacturing, service, and sales. Nevertheless, with the development of AI technology, this may increase to include the whole product life cycle, both during the initial design and post market service. GenAI would streamline BOM creation and updates in the future, but would also be used to, among other things, improve the design processes by incorporating AI-assisted design tools. Such tools may assist engineers to make the best use of product design as per the manufacturing constraints, availability of material, and cost analysis, which will make the time to market even shorter.

In addition, predictive analytics based on AI may improve all lifecycle stages. As an example, some supply chain disruption, manufacturing delays, or maintenance requirements can be predicted before they happen, which will allow organizations to preempt these problems and maintain the constant supply of products with high performance and quality.

2. Increased Customization and Personalization
As AI steps forward, BOM systems would be able to support a product of extreme customization and personalization, timely and cost-efficaciously. GenAI can be used in a system where complex, customer-specific BOMs are managed in industries where the products are customized to the specifications of individual customers, i.e., in the automotive industry, aerospace industry, or high technology consumer products. The future of AI is the capability to generate custom BOMs swiftly, depending on the requirements of the customer, dynamically change designs and configurations in real time, and make sure that all the parts of the product and systems are compatible.

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3. Integration with Other Emerging Technologies

GenAI coupled with other emerging technologies, such as Internet of Things (IoT), blockchain, and digital twins, is the way to go in BOM management. Sensors integrated into products via IoT would bring real-time data to the BOM systems to enable the manufacturer and service teams to be more responsive in not only product performance but also product maintenance requirements. BOM data could be secured and authenticated with the help of blockchain technology, which would provide transparency and traceability of product lifecycle. Also, physical products could be represented by digital twins that are linked with the BOM systems and simulate and test product performance, detecting the possible problems before they would appear in real-life manufacturing or service.

4. Continuous Learning and Improvement

Due to the continuous learning of AI systems based on the available data, the BOM management will become smarter as time goes by. GenAI could be utilized to not only automate something but also to improve upon its functionality through learning about previous errors, discovering new areas of inefficiency and make recommendations. The network effect will enable the AI-driven BOM systems to evolve as a result of shared experience, enabling them to become more intelligent and effective solutions as more companies start using these systems.

To sum up, GenAI has the potential to shape the future of the BOM management. With the improvement in technology, it will not only increase the efficiency and accuracy of the BOM systems but also help in smart and more sustainable product development processes. GenAI combined with the other technologies, greater personalization, and lifelong learning will characterize the next generation of BOM management systems and provide organizations with the tools they require to succeed in the ever-more competitive and complex business environment.

V. CONCLUSION AND FUTURE WORK

To sum up, the introduction of Generative AI (GenAI) to the process of Bill of Materials (BOM) management has become a groundbreaking approach to the persistent issues of data disaggregation, ineffectiveness, and manual work that are prone to error in engineering, manufacturing, service, and sales operations. Conventional BOM management systems have the tendency of creating siloed data, version inconsistencies and manual redundancy, which are counterproductive towards collaboration, and delay the product development life cycle. GenAI can help automate the creation, reconciliation and maintenance of BOMs that can simplify these processes, thereby guaranteeing timely availability of correct and consistent data to all parties involved.

The structure of GenAI proposed in the current paper demonstrates how it can unite the isolated BOM perspectives and support decision-making in the product lifecycle by providing timely, unbiased and high-quality data. Automation of BOM and real-time reconciliation of various departmental viewpoints goes a long way in mitigating any case of error and delay thus enhancing the time-to-market of a product. Also, GenAI provides higher quality of data, which is important to ensure the integrity of products and prevent the expensive errors in the production or service.

Although the idea of AI-driven BOM systems has a bright future, the introduction is not without certain difficulties. Implementing AI into the current infrastructure is complicated, requires high-quality training data, and the issues of data security and privacy require to be solved to implement it successfully. Nevertheless, with the development of AI technologies and the increasing experience of organizations with such systems, the advantages of GenAI in the sphere of BOM management will also increase and provide more efficient and scalable systems with a greater number of options.

In the future, the possible expansion of GenAI in the management of BOM is its additional functionalities to cover the full lifecycle of the product, increased personalization to the needs of particular clients, and integration with other emerging technologies, including IoT, blockchain, and digital twins. In general, GenAI can transform BOM management, and eventually, it will make the manufacturing industry more efficient, innovative, and competitive.

REFERENCES

1. A. Alqahtani, S. Banitaan, and S. Banitaan, "A systematic literature review of software risk management for global software development," in *2017 IEEE/ACS 14th International Conference on Computer Systems and Applications (AICCSA)*, 2017, pp. 1310–1317. [Online]. Available: https://doi.org/10.1109/AICCSA.2017.71.

2. I. Barclay, A. Preece, I. Taylor, S. Krishnakumar Radha, and J. Nabrzyski, "Providing assurance and scrutability on shared data and machine learning models with verifiable credentials," *Concurrency and Computation: Practice and Experience*, vol. 35, no. 18, e6997, 2023.

3. I. Barclay, A. Preece, I. Taylor, and D. Verma, "Towards traceability in data ecosystems using a bill of materials model," *arXiv preprint arXiv:1904.04253*, 2019.

4. C. Benedetti, F. Cofano, et al., "The Impact of SBOM Generators on Vulnerability Assessment in Python: A Comparison and a Novel Approach," in *International Conference on Software Engineering and Security*, Springer, 2024, pp. 1–12. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-031-95764-2_19.

5. K. Bennet, G. Krishnan Rajbahadur, A. Suriyawongkul, and K. Stewart, "Implementing AI Bill of Materials (AI BOM) with SPDX 3.0," The Linux Foundation, 2024. [Online]. Available: https://doi.org/10.70828/RNED4427.

6. K. Blind and M. Böhm, "The Relationship Between Open Source Software and Standard Setting," Technical Report JRC116106, European Commission, 2019. [Online]. Available: https://publications.jrc.ec.europa.eu/repository/handle/JRC116106.

7. Center for Devices and Radiological Health, "Cybersecurity in Medical Devices: Quality System Considerations and Content of Premarket Submissions," 2025.

8. European Commission, "The relationship between open source software and standard setting," Publications Office, LU, 2019. [Online]. Available: https://doi.org/10.2760/163594.

9. Coalition for Secure AI, "SAIF Risk Assessment: A new tool to help secure AI systems across industry," 2024. [Online]. Available: https://www.coalitionforsecureai.org/googlesaif-risk-assessment/.

10. SPDX contributors, "SPDX Meeting Notes," 2024. [Online]. Available: https://github.com/spdx/meetings/tree/main/ai.

11. S. Coughlan, "OpenChain Work Groups– New and Improved Structure," OpenChain Project, 2022. [Online]. Available: https://openchainproject.org/news/2022/10/12/wg-structure.

12. Cybersecurity and Infrastructure Security Agency (CISA), "2025 Minimum Elements for a Software Bill of Materials (SBOM) Public Comment Draft," 2025. [Online]. Available: https://www.cisa.gov/resources-tools/resources/2025-minimumelements-software-bill-materials-sbom.

13. Cybersecurity and Infrastructure Security Agency (CISA), "Software Bill of Materials (SBOM) Sharing and Use: A Guide for Organizations," Technical Report, U.S. Department of Homeland Security, 2023. [Online]. Available: https://www.cisa.gov/resources-tools/sbom-sharing-and-use-guide.

14. DMSC (n.d.) Overview of the Quality Information Framework (QIF) Standard. Digital Metrology Standards Consortium. Available at: https://qifstandards.org/ (accessed 24 January 2026).

15. Garcia, C.I., DiBattista, M.A., Letelier, T.A., Halloran, H.D. and Camelio, J.A. (2024) 'Framework for LLM applications in manufacturing', Manufacturing Letters, 41(Supplement), pp. 253–263. https://doi.org/10.1016/j.mfglet.2024.09.030.

16. Helu, M., Hedberg Jr., T. and Barnard Feeney, A. (2017) 'Reference architecture to integrate heterogeneous manufacturing systems for the digital thread', CIRP Journal of Manufacturing Science and Technology, 19, pp. 191–195.

17. ISO (2020) ISO 10303-242:2020 Industrial automation systems and integration – Product data representation and exchange – Part 242: Application protocol: Managed model-based 3D engineering. International Organization for Standardization. Available at: https://www.iso.org/standard/66654.html (accessed 24 January 2026).

18. ISO (2020) ISO 23952:2020 Automation systems and integration – Quality information framework (QIF) – An integrated model for manufacturing quality information. International Organization for Standardization. Available at: https://www.iso.org/standard/77461.html (accessed 24 January 2026).

19. ISA (n.d.) ISA-95 Standard: Enterprise-Control System Integration. International Society of Automation. Available at: https://www.isa.org/standards-and-publications/isa-standards/isa-95-standard (accessed 24 January 2026).

20. Kasper, N., Pfenning, M. and Eigner, M. (2024) 'The digital thread for system lifecycle management with a native graph database in a polyglot architecture', Proceedings of the Design Society, International Design Conference – DESIGN 2024. https://doi.org/10.1017/pds.2024.210.

21. Kwon, S., Kim, J., Hedberg Jr., T. and Fischer, L. (2020) 'Enriching standards-based digital thread by fusing as-designed and as-inspected data using knowledge graphs based on ontology', Advanced Engineering Informatics, 45, 101102. https://doi.org/10.1016/j.aei.2020.101102.

22. Listl, F.G., Fischer, J., Sohr, A., Dittler, D., Jazdi, N. and Weyrich, M. (2023) 'Utilizing ISA-95 in an Industrial Knowledge Graph for Material Flow Simulation – Semantic Model Extensions and Efficient Data Integration', Procedia CIRP, 123, pp. 241–246. https://doi.org/10.1016/j.procir.2023.09.214.

23. NIST (n.d.) NIST STEP to OWL Translator (STP2OWL). National Institute of Standards and Technology. Available at: https://github.com/usnistgov/stp2owl (accessed 24 January 2026).

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||Volume 9, Issue 1, January-February 2026||

DOI:10.15662/IJRPETM.2026.0901005

24. Prostep iViP Association (2023) 'Bill of Materials (BOM): semantics and practice – Fact Sheet'. prostep ivip Association. Available at: https://www.prostep.org/mediathek/fact-sheets/iso-10303-242 (accessed 24 January 2026).
25. Standfield, B., Holterman, E. and Waddell, R. (2024) Spatial and Temporal Data Alignment from Disparate Sources for Feature Association. NIST Grant/Contract Report (NIST GCR) 24-050. https://doi.org/10.6028/NIST.GCR.24-050.
26. Wan, Y., Liu, Y., Chen, Z., Chen, C., Li, X., Hu, F. and Packianather, M. (2024) 'Making knowledge graphs work for smart manufacturing: Research topics, applications and prospects', Journal of Manufacturing Systems, 76, pp. 103–132. https://doi.org/10.1016/j.jmsy.2024.07.009.
27. Wang, Y., Ren, W., Zhang, C. and Zhao, X. (2022) 'Bill of material consistency reconstruction method for complex products driven by digital twin', International Journal of Advanced Manufacturing Technology, 120, pp. 185–202. https://doi.org/10.1007/s00170-021-08603-0.
28. Wang, Y., Wang, Y., Ren, W. and Jiang, Z. (2024) 'Knowledge driven multiview bill of material reconfiguration for complex products in the digital twin workshop', International Journal of Advanced Manufacturing Technology. https://doi.org/10.1007/s00170-023-12885-x.
29. Zhao, X., Wei, S., Ren, S., Cai, W. and Zhang, Y. (2024) 'Integrating MBD with BOM for consistent data transformation during lifecycle synergetic decision-making of complex products', Advanced Engineering Informatics, 61, 102491. https://doi.org/10.1016/j.aei.2024.102491.