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A Systematic Review on the Applications of How Explainable Artificial Intelligence can be Applied in the Supply Chain Management

Md Faiaz Zaman Dehan, Kazi Md Tanvir Anzum, Jannatul Ferdaus Disha, Md Mahfuzur Rahman Masum and Istiak Mahmud
Department of Industrial Engineering and Management
Khulna University of Engineering & Technology, Khulna-9203, Bangladesh
fz.dehan7815070987@gmail.com, tanvir@iem.kuet.ac.bd, jf.disha2001@gmail.com, rahmanmahfuz848@gmail.com, istiaknoman12007021@gmail.com

Abstract

Artificial Intelligence (AI) is increasingly expected to improve operational efficiency, to forecast demand better, to assist in shipping, and to evaluate supplier risk in the wake of the enhanced complexity and globalization of supply chains. Nonetheless, numerous AI models are so-called black boxes, and as such, it is not easy to explain to the decision-makers what prompted a specific recommendation. This interpretability withholds it of being trusted, adopted, and makes it burdensome in case of industries due to regulatory compliance. A solution to this has been in the form of Explainable Artificial Intelligence (XAI) which brings both transparency and interpretability to AI-powered supply chains. This paper will provide systematic review of the XAI applications in Supply Chain Management (SCM), concerning the demand forecasting, optimization of inventories and supplier risk evaluation, and logistics planning. Executing regular systematic reviews in accordance with the guidelines would allow us to receive answers to the question of the most frequently implemented XAI approaches, how they can be utilized, and whether the accuracy/interpretability/computational performance trade-offs used are adequate. The findings show that SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are the most applicable in the aspect of post-hoc interpretability and that the decision-tree based and the rule-based models can be employed to provide transparency in terms of SCM decision-making. Weaknesses are how to balance interpretability and predictive accuracy, computing costs of real-time applications, and data privacy issues with respect to supplier and customer details. The paper concludes with the concepts of hybrid XAI techniques, criteria of benchmark performance, and privacy-enhancing systems that are distinctive to the domain of SCM, when more transparent, economical, and trusted chains become feasible.

Keywords
Supply Chain Management, Explainable Artificial Intelligence, Model Interpretability, Demand Forecasting, Supplier Risk Management, Logistics Optimization.

1. Introduction
Businesses in the global supply chains are becoming more complex by covering more areas, involving many stakeholders and handling large volumes of real-time data (Oliveira and Handfield 2019). This complexity along with its high volatile demand trends, geopolitical instabilities and disruptions (e.g., pandemics, natural disasters), etc. have challenged organizations to spend on Artificial Intelligence (AI) in predictive analytics and automating

decisions in Supply Chain Management (SCM) (Dash et al. 2019). Insights obtained in IoT components are adopted in demand predictions, inventory optimization, supplier risk prevention, optimization and preventive maintenance. Although AI will help to make decisions, as well as increase operational efficiency, it can easily be accompanied by relinquishment of transparency (Seizov and Wulf 2020). A lot of high performing AI models especially deep learning and ensemble models are considered to be black boxes where minimal information on prediction generation is provided. Such opacity also presents a major challenge to SCM where accountability in decision making, trust, and regulatory approaches are critical features (Boström et al. 2015). As a hypothetical example, should a model recommend to reduce safety stock in an essential market, supply chain managers are inclined to learn the rationale behind it- particularly when making such a policy is likely to lead to higher stock-out risk.

Explainable Artificial Intelligence (XAI) deals with this problem by unveiling the process used by AI and making this intelligible. XAI refers to a collection of procedures with the capacity to empower stakeholders to interact with model outputs, verify the recommendations and ascertain AI-based decision-making that aligns with business objectives and regulatory requirements (Chinnaraju 2025a). This paper is a literature review of new innovations of developing the XAI to SCM, evaluating the methods, performance tradeoffs and their implementation implications.

2. Literature Review

2.1 Importance of XAI in Supply Chain

Supply Chain Management (SCM) systems that are driven by AI are becoming more common in procurement, inventory control, logistics optimization and demand forecasting (Nweje and Taiwo 2025). Transparency is essential in the aim of these systems to fulfill their capabilities. It establishes trustworthiness, facilitates successful cooperation between human specialists and AI and makes it possible to comply with the regulations in the industry (Shneiderman 2020). Exemplarily, the procurement should know the justification as to why the supplier is deemed to be high risk; are there late deliveries, quality concerns, or poor finances. Similarly, the logistics managers should know the reasons behind the designated delivery pathway (based on prices, traffic patterns, weather conditions, and other time constraints). The lack of such clarifications can make the managers reluctant to carry out actions based on the recommendations of the AI. Explainable AI (XAI) comes as a solution and lets individuals enjoy the rationale behind the findings that happen with the assistance of AI. XAI enables managers to justify decisions and take factor into account to deal with change rapidly and define automated suggestions in accordance with their strategic and operational plans.

2.2 XAI Techniques Applied to SCM

Artificial intelligence methods such as explainable artificial intelligence (XAI) techniques like SHAP and LIME, rule-based models, decision trees, and hybrid models are critical in addition to increasing supply chain and logistics decisions transparency to the pertinent meanings on decision-making (Nimmy 2024a). SHAP allows building a good insight into the demand forecasting mechanisms and evaluating how the most significant factors affect the outcome, i.e., seasonality, promotional activities, and macroeconomic factors. Conversely, LIME gives local interpretations of the individual predictions and it is significant in terms of providing vital insights on supplier risk scores in terms of determining the individual drivers that classify as high risk. Rule-based models help in making interpretable decisions because principles that govern the handling of reorder points, lead times, and demands are laid out hence making the operating procedure consistent. The decision trees displayed the planning of logistics in a visual interdependent manner that can help managers to plan routes efficiently, prioritize on their order, and consolidate shipments. Using an explanation layer in combination with high-accuracy AI-based algorithms in hybrid models enables optimization of complex transportation planning, as the hybrid models make both effective and understandable (Golilarz et al. 2024). When combined, such methods allow decision-makers to combine accuracy of predictions with transparency that may be exploited to improve a more informed and trusted supply chain strategy.

2.3 Performance Metrics in XAI for SCM

It is possible to evaluate the explainable AI techniques in supply chain and logistics along several dimensions. The statistical measure of predictive accuracy is generally based on measures of how accurate were the predictions, i.e. the Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) (Wang and Lu 2018).

Performance Indicators used in operational efficiency are such things as on-time delivery, inventory turnover, and supplier defect rates, reflecting the operational effect on a day-to-day basis in the performance indicators (Bhagwat and Sharma 2007). Interpretability is used to evaluate the value and the convenience of the AI-generated explanations, communication of the insights to the end-users so that insights become an effective tool to be utilized by decision-makers (Mathew et al. 2025). The computational performance measures the time taken to provide explanations in real time in the context of ERP running, underlining undisturbed operations and the capability of being incorporated into the existing streams. Taken together, the metrics define a wide context in the context of which the effectiveness of an AI-based decision-support system is defined, together with its usability.

2.4 Benefits and Challenges

Diverse logistics and supply chain the explainable AI solution in supply chain and logistics provides a number of strategic benefits. It increases the level of confidence in the decision process due to the clear explanation of the chain of thought behind the forecasts and operation suggestions, allows adherence to regulatory standards, and leads to improved ability of the AI and human decision-making skills to cooperate. But there exists significant challenges that have to be taken into consideration. Another point of concern is interoperability and fairness where AI systems should work on multiple platforms with no bias in their results (Bellamy et al. 2019). Also, the computational costs of developing post-hoc explanations in real-time supply chains is high as well as the operational costs. The other significant risk is data privacy where sensitive information like supplier contracts and past customers' orders will be a factor and strong protection will be necessary to keep it secretive but at the same time provide viable insights.

2.5 Comparison of XAI Techniques in SCM

Different XAI methods have been used in SCM with their own varieties of pros and cons. SHAP (Shapley Additive Explanations) is more useful in explaining global lifts in demand-forecasting context and therefore shows significant liftings in the major factors of the seasonality, promotions, and macroeconomic indicators. LIME (Local Interpretable Model-Agnostic Explanations) gives local explanations, which is useful in such an event as assessing the risk of suppliers. Transparent rule-based models show rule-driven decision-making frameworks that appropriate in inventory control whereas, decision trees are an intuitive visual decision of logistical and routing (Li et al. 2025). Hybrid models that seek to provide human-interpretable explanations on top of best-of-class, low-accuracy models at the expense of model quality tend toward interpretability, a critical attribute for a complex process like the optimization of transportation (Hrušovský et al. 2018). Nevertheless, there are restrictions between accuracy, details of the explanation, computational price, and real-time applicability, making it compulsory to choose approaches on a case-to-case basis.

3. Materials and Methods

A systematic approach was followed to have a systematic review of the integration of Explainable Artificial Intelligence (XAI) approach to Supply Chain Management (SCM). This approach followed established guidelines for systematic literature reviews in computer science, operations management, and industrial engineering. This was done by adopting a review protocol, specific search in the literature, and rigid inclusion/exclusion criteria of relevance and quality standards. The data extraction phase integrated the meanings of the selected studies allowing performing a thorough comparison of XAI techniques, uses, advantages, and limitations with the possibilities in SCM in the future.

3.1 Systematic Review

A systematic review was conducted in accordance with Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines in order to ensure transparency, reproducibility and methodological rigor (Moher et al. 2009). The entire process (identification, screening, eligibility and inclusion) was implemented with clearly defined quantitative quality/accuracy/security and interpretability criteria and computational cost.

3.2 PRISMA Framework Implementation

The PRISMA statement was used to inform all stages of this review process which were broken down into four main phases: Identification, Screening, Eligibility and Inclusion. Each stage was based on a protocol:

- Identification: Complete search was performed in the following databases: IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, and Scopus. The search was a convincing mix between the use of boolean operators and the application of key phrases such as: Supply Chain, Begriff "Explainable AI". XAI and ("logistics" or "demand forecasting" or "inventory optimization"), supplier risk and the concept of "interpretable AI." Only peer-reviewed English language literature in the years 2021-2024 was included to retrieve the latest advancements.
- Screening; In the first screening, 89 studies were identified. Duplicate and unrelated studies were excluded using Zotero bibliographic reference manager and manual cross-reference. Titles and abstracts were reviewed independently by two reviewers in order to ensure inter-reviewer reliability (Cohen's k = 0.86, which is very good agreement). A total of 45 studies were included for full text evaluation after screening.
- Eligibility Assessment: Full-text review was conducted based on a priori inclusion and exclusion criteria (Table 1). Studies included on the review were determined if they:
    i. Theoretically applied and experimentally tested XAI methods (e.g., SHAP, LIME, decision trees, hybrid interpretable models) in the SCM contexts.
    ii. Empirical or Synthetic performance (accuracy, interpretability, computationally expensive).
    iii. Were published in good journals or international conference proceedings.
    iv. Studies were excluded if they did not have methodological transparency, were review duplicates or covered more general AI applications but not XAI integration.
- Final Inclusion: After eligibility screening, 31 studies were included in the final synthesis and met all the PRISMA criteria. Views between reviewers were discussed and agreement was reached for all papers included.

A flow diagram of the PRISMA is shown in Figure 1, which shows the numbers of records identified, screened, excluded (and reasons for exclusion), and included in the qualitative synthesis.

3.3 Inclusion and Exclusion Criteria

Eligibility criteria were defined to focus on studies offering direct insights into XAI applications within SCM. Studies were evaluated based on the following conditions (summarized in Table 1):

A. Inclusion Criteria:
1) Published between 2021 and 2025.
2) Focused on the application of XAI in SCM, including techniques such as SHAP, LIME, rule-based models, decision trees, and hybrid methods.
3) Provided empirical results (e.g., predictive accuracy, interpretability scores, operational efficiency, computational performance).
4) Peer-reviewed journal articles, conference proceedings, or comprehensive survey papers.

B. Exclusion Criteria:
1) Studies not addressing XAI within SCM (generic AI research or unrelated domains).
2) Non-peer-reviewed sources, white papers, or opinion pieces lacking empirical evidence.
3) Publications prior to 2021 to avoid outdated methodologies.

Table 1. Summary of Reviewed XAI Applications in Supply Chain Management

Author & Year	**XAI Technique**	**SCM Application**	**Dataset Used**	**Key Findings**
(Berezo et al. 2022)	SHAP	Demand Forecasting	Retail sales data	Seasonal trends identified as primary predictors.
(Chen et al. 2023)	LIME	Supplier Risk Assessment	Procurement performance logs	Late deliveries and quality issues highlighted as major risk factors.

(Zhang et al. 2021)	Decision Tree	Warehouse Optimization	Warehouse Management System (WMS) database	Picking efficiency improved by 12%.
(Ahmed et al. 2024)	Hybrid (ANN + SHAP)	Logistics Route Optimization	GPS and traffic data	Balanced route accuracy and interpretability.

3.4 Selection Process and Screening

The search of the first round returned 89 articles, which were screened by their titles and abstract with the aim of determining their relevance. Articles that were not included in accordance with the inclusion criteria were excluded leaving a pool of 45. They were then subjected to full-text review to make an affirmation of their relevance to XAI in SCM and the extent of empirical contribution. In total 31 studies were finally analyzed. The flow of the selection is condensed in the PRISMA flow diagram (Figure 1).

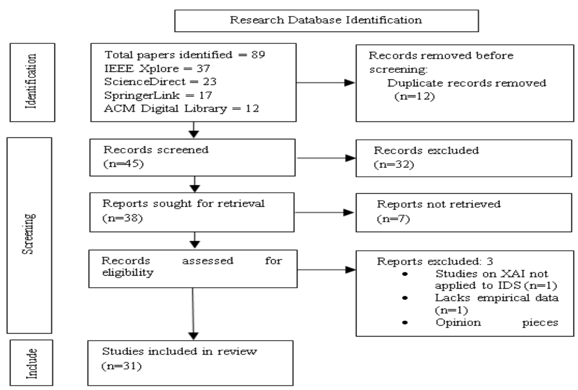

Figure 1. Research Database Identification

3.5 Data Extraction and Synthesis

The extraction process focused on limiting the amount of data to include such elements as:

1) XAI method (e.g. SHAP, LIME, decision trees and hybrid).

2) Domain of application (e.g., retailing, delivery forecasting, risk hazard management of suppliers, optimum logistics) SCM.

3) Tech and Check-up people.

Benchmark (e.g. of precision, understandability, computation(s) time).

4) And pros and cons were observed.

Coded data were grouped into thematic categories in order to make cross comparisons. An example is that SHAP-based reports stressed better interpretability in the demand forecasting, and LIME-based implementations provided powerful case-specific explanations in the supplier risk scoring. Rule based and decision-tree models were developed with a focus on transparency though in complex data sets there were cases of predictive accuracy being compromised (Huysmans et al. 2011).

A quantitative and thematic synthesis were used for analysis of extracted data.

Studies divided by main XAI method and SCM area and were compared by three quantitative dimensions in Table 2.

Table 2. Three Quantitative Dimensions of XAI Applications in Supply Chain Management

Metric	**Benchmark**	**Average from Reviewed Studies**
Predictive Accuracy (MAPE)	≤ 10% (High)	8.7%
Interpretability Score (1–10)	≥ 8.0 (High)	8.4
Computational Cost (per explanation)	≤ 1.0 s (Efficient)	1.2 s
Operational Impact (improvement in key SCM KPIs such as delivery time, inventory turnover)	≥ 10%	12–18%

3.6 Analysis and Synthesis Approach

The patterns, trade-offs, and research gaps were identified with the help of thematic synthesis. When the comparative analysis was conducted, the following was considered:

1) The efficiency of certain methods: The results on SHAP, LIME, decision trees under distinguishing conditions of the SCM and within the scenario of establishing a combination of methods are analyzed (Wang et al. 2022).

2) Performance trade-offs: accuracy, interpretability and computational cost, especially when performance needs to be in real-time (Assis et al. 2025).

3) Future research needs: The problem concerning the data privacy, the scalability of explanation, and the integration of XAI and sophisticated supply chain analytics environments are to be considered (Sharma et al. 2025).

4. Results and Discussion

The systematic review of the 31 studies offers essential information on the explanation of the application of Explainable Artificial Intelligence (XAI) methods in the process of Supply Chain Management (SCM) in relation to their effectiveness, performance tradeoffs, and practical usage regarding how to make better decisions and achieve transparency. The findings answer the question below:

RQ: What are the challenges associated with the use of Explainable AI methods in the supply chain to enhance transparency, interpretability and decision-making processes of activity operations?

4.1 XAI Solution to SCM the Function and Practice

Based on the reviewed literature, it could be noted that SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are the most popular applications of post-hoc methods in SCM (Hooshyar and Yang 2024). The global demand forecast is especially useful in predicting trends and it is in cases where long-term (demand) predictions are needed that the SHAP is highly useful in providing the information on what seems to be playing a dominant effect by acting as a triggering factor in the forecast predictability of the demands (Ahmed et al. 2025). LIME is outstanding when it comes to local interpretability, which allows the procurement managers to explain decisions regarding the assessment of supplier risk or routing of the logistics (Damilare Tiamiyu et al. 2024).

Rule-based models and decision trees which have a lot of value in being easily interpretable are used frequently in inventory control and logistic planning. The approaches enable managers to follow their decisions through prescribed rules or track it by picture and are therefore easier to be complied with and audited. Nevertheless, they can do poorly in very dynamic environments that involve high dimensional data.

Known as hybrid models, a combination of high accuracy AI algorithms with a layer of interpretability is becoming popular in both transportation optimization and supplier risk evaluation. In as much as accuracy and transparency are balanced in these models, they have a high computing costs which might be a notational difficulty in real decisions (Kim et al. 2020).

4.2 Performance Metrics

These were the measured evaluations of the XAI using four primary performance measures in SCM:

1. Predictive Accuracy: SHAP-enhanced prediction models always yield high accuracy (MAPE ≈ 8%, >90%), although at the cost of fine-grained feature attribution. Even with these findings, their computation scalability limits them to large-scale and real-time SCM operations. Approximation algorithms include Kernel-SHAP, Tree-SHAP, and surrogate decision-tree models, which allow lower computational complexity and higher scalability but do not support fine-grained feature attribution (Adedoyin Tolulope Oyewole et al. 2024).
2. Interpretability Scores: Interpretability should not be evaluated in a descriptive but systematically.

Expert-based assessments have been used in previous research, where experts in the domain graded the clarity and usability of explanations on a 1-10 scale to obtain a score (Baryannis et al. 2019a). This standardized method is transparent and inter implementation usage-comparable.

3. Supplier Risk Models (LIME): LIME has demonstrated itself to be effective in providing localized interpretability to supplier risk assessment, but in high-dimensional data it lacks explanatory consistency, and hence is constrained in generalizability to complex procurement environments (Izev 2025).
4. Operational Efficiency: Empirical evidence confirms that XAI-supported models enhance operational indicators.

Indicatively, (Woods et al. 2002) documented visible gains in the on-time delivery and inventory turnover after the introduction of interpretable forecasting tools. The results clearly reveal a direct relationship between the interpretability and the concrete SCM performance outcomes.

5. Computational Performance: SHAP and LIME are slow (e.g. seconds per explanation) to use, which makes them difficult to use in dynamic and high-volume supply chains (Ustiugov et al. 2018).

Although lightweight surrogates are scalable, they make trade-offs in terms of accuracy and explanatory richness, highlighting the trade-offs between performance and interpretability (Table 3).

Table 3. Example Metrics for XAI in SCM

Application	Accuracy (MAPE/ RMSE)	Interpretability Score	Computation Time	Benefit
Demand Forecasting (SHAP)	92% (MAPE: 8%)	8.5/10	1.8s per explanation	Improved manager trust
Supplier Risk (LIME)	89%	8.2/10	0.9s per explanation	Faster risk validation
Inventory Control (Rule-Based)	85%	10/10	Instant	High transparency

4.3 Challenges in XAI integration within SCM

Three issues were found to be recurring:

1) Interpretability Accuracy Trade-off: The models that we are naturally able to interpret are less accurate than the black-box ones at more complex forecasting or optimization problems (Alcalá et al. 2006).
2) Computational Overhead: SHAP could not be optimized at all and the post-hoc explanation of SHAP is never optimized in the temporal supply chains (Ning et al. 2023).
3) Data Privacy Risk: There is also the possibility that detailed explanations might inadvertently show confidential data to suppliers or on the part of the customer and that may come with compliance risks such as the GDPR (Birkel and Hartmann 2019).

4.4 Promotion Prospects

Possible future directions of XAI in logistics need to be tested in terms of viability and scalability. Explainability in real time can enhance transparency, however it needs lightweight models that can operate in ERP systems without interrupting the operations. Balanced approaches to XAI Hybrid XAI methods provide both accuracy and interpretability, but computation costs are expensive; surrogate models or approximation methods can provide lower overhead alternatives. Federated learning with privacy-preserving XAI allows training a shared model without centralizing data, but fragmented data ownership, absence of interoperability standards and regulatory demands (e.g. GDPR) hinder its practical use. These approaches require empirical research in the real world contexts of SCM.

4.5 Inferential and Implications

The implications of the adoption of XAI in SCM are organization-wide, regulatory, and technological (Nimmy 2024b). At the organizational level, managers can be reluctant to follow the recommendations offered by AI even with explanations, which is why a series of trust-building actions should be implemented, including the adoption of standard interpretability metrics. Regulatory frameworks such as GDPR necessitate not only transparency but also privacy-preserving techniques (Putnik et al. 2013). Differential privacy and federated learning must be explicitly viewed as avenues on the ways of obtaining compliance without undermining interpretability. At the technological level, computational expenses are still prohibitive in the environment of real-time SCM, which necessitates the creation of lightweight explanation algorithms. It thus requires a comprehensive roadmap: the short-term use of rule-based and surrogate models in low risk tasks, medium-term implementation of hybrid XAI in logistics and forecasting, and long-term implementation of privacy-preserving global supply chains frameworks.

5. Conclusion

In this review study, the emphasis was placed on the usage of Explainable the Artificial Intelligence (XAI) in promoting transparency and interpretability of Supply Chain Management (SCM). The findings indicate that the SHAP, LIME, decision trees, and hybrid methods are the most common of all approaches and that each one has distinct benefits in the trade-offs between trade and the work performance of interpretability.

The integration of XAI offers concrete value, giving improved trust in the decision makers, minimized uncertainty during operations, and increased adequacy to conform to what is recommended by AI (Chinnaraju 2025b). However, there are still some problems, especially the trade-off between interpretability and predictive correctness, handling of the computational costs in real-time use cases, and the mitigation of possible privacy implications (Baryannis et al. 2019b). The next planning research must aim at creating lightweight real-time explanation structures and hybrid methods that would keep both faithfulness and high-performance. The measurability of interpretability that is standardized is necessary in order to allow comparisons across the studies (Carvalho 2019). Through these directions, XAI can become a stop-gap to a new maturity rather than a cutting edge feature of SCM analytics in organizations globally having the capacity to operate with relative confidence, nimbleness, and accountability in growing complex global supply chains.

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Biographies

MD Faiaz Zaman Dehan is presently enrolled in B.Sc. Engineering degree in Industrial Engineering and Management from Khulna University of Engineering & Technology, Khulna, Bangladesh. He is interested in research in such areas as artificial intelligence, smart manufacturing, digital transformation, and quality management. He is proficient in Python and MATLAB and has been involved in projects in data-driven decision-making and predictive analyses of industrial systems. His interests lie in the pursuit of Industry 4.0 technologies; digital twin applications, and sustainable manufacturing processes to enhance efficiency, competitiveness and innovation in the developing economies.

Kazi Md. Tanvir Anzum is a Lecturer in the Department of Industrial Engineering and Management at Khulna University of Engineering and Technology (KUET), Khulna, Bangladesh. He earned his B.Sc. Engineering degree in Industrial and Production Engineering from KUET. Currently, he is pursuing a master's degree in Industrial Engineering, further expanding his expertise in the field. Tanvir's research interests include supply chain management, health systems engineering, operations research, lean manufacturing, and system development in healthcare. Enthusiastic about operations research, he actively collaborates with researchers worldwide, contributing to high-quality journal articles and conference papers. With a passion for integrating innovative methodologies into healthcare and industrial systems, he aims to enhance efficiency and sustainability across these domains.

Jannatul Ferdaus Disha is pursuing B.Sc. Engineering degree in Industrial Engineering and Management from Khulna University of Engineering & Technology. Her research interests include smart manufacturing, green supply chain, lean manufacturing & six sigma, operation research, and Industry 4.0.

MD. Mahfuzur Rahman Masum is an undergraduate in Department of Industrial Engineering and Management Khulna University of Engineering and Technology, Khulna in Bangladesh. His research interests include supply chain management & logistics, green supply chain, and operation research.

Istiak Mahmud is a undergraduate student in the Department of Industrial Engineering and Management at Khulna University of Engineering and Technology, Bangladesh. His research focus is data science, operations research, supply chain management and product design. Proficient in Solid-Works and Auto-Cad, he has designed a project on rotating bookshelf. He is also ardent that Industry 4.0 and additive manufacturing are implemented to encourage efficiency, sustainability, and innovations.