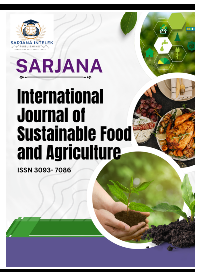
SARJANA INTELEK PUBLISHING
PUBLISHING THE FUTURE TODAY

Sarjana International Journal of Sustainable Food and Agriculture

Journal homepage:
https://sarjanaintelek.my/index.php/sijsfa/index
ISSN: 3093-7086



When Cost-Based ABC Fails: Inventory Prioritisation in Perishable Food Manufacturing

Nor Fyadzillah Mohd Taha[1], Nur Izzah ‘Atirah Muhd Faizal[1,*], Mohd NajibAbdul Ghani Yolhamid[1], Hani Kalsom Hashim[1]

[1] Fakulti Sains dan Teknologi Pertahanan, Universiti Pertahanan Nasional Malaysia, Kem, Sungai Besi, 57000 Kuala Lumpur, Malaysia

ARTICLE INFO

Article history:
Received 8 January 2026
Received in revised form 27 February 2026
Accepted 13 March 2026
Available online 21 April 2026

Keywords:
Inventory classification; ABC analysis; Food manufacturing; Perishability; Demand volatility; Qualitative study

ABSTRACT

Changes in demand, short product lifespans, strict quality control requirements, and temperature sensitivity are challenges in the perishable food manufacturing environment. Many businesses continue to use cost-based ABC inventory classification systems, which assume stable demand patterns and fixed item priorities, even though operating conditions are constantly changing. However, these static methods often do not directly reflect changing operational risks. How are inventory priorities determined when cost-based ABC systems no longer meet operational needs? Practitioners from three food manufacturing companies in Malaysia were interviewed using semi-structured interviews in this study, employing a qualitative exploratory design. Inductive thematic analysis was used to examine the data to identify decision patterns and elements that influence inventory criticality. The study found three main aspects: instability of inventory priorities due to demand fluctuations, risks arising from the production process, and the perishable nature of products. The study's findings also included implicit consideration of various criteria based on the practitioners' experience. The results of the study indicate that inventory priorities change according to the risks of the current situation and are not solely based on historical costs. An adaptive priority cycle model is proposed to organize this decision-making logic in a more systematic way.

1. Introduction

The production of perishable food faces many operational challenges, including a short product shelf life, strict food safety requirements, sensitivity to temperature, and unpredictable demand patterns. These characteristics increase the likelihood of product spoilage, production problems, and inventory build-up. Therefore, more meticulous, and responsive inventory control mechanisms are highly necessary. Ding and Peng [1] developed a heuristic model for perishable product inventory systems in the context of mixed production policies. The patterns of spoilage and the restocking lead time affect service levels and waste reduction, as demonstrated by this model. Furthermore, Leithner and Fikar [2] used simulation modeling to integrate quality data into the fresh food supply chain. They found that access to more comprehensive information improves the quality of operational

* *Corresponding author.*
E-mail address: atirahizzah17@gmail.com

decisions. As stated by Murala *et al.* [3], Internet of Things-based traceability systems are an essential component in enhancing transparency and sustainability in perishable product supply chains.

Existing studies on perishable inventory systems mainly focus on modelling components and technological support. However, research still focuses more on directly understanding how industry practitioners set inventory priorities under uncertain operating conditions rather than system optimization and technological improvements. Demand uncertainty makes this problem more complex. Shanker *et al.* [4] examined the resilience of the supply chain for perishable products during a crisis. In contrast, Shin *et al.* [5] proposed a two-tier inventory model to address demand uncertainty in production planning. Although this study acknowledges operational instability, it still focuses on optimization and does not examine how inventory priorities are dynamically adjusted when formal systems cannot meet urgent industry needs.

Because ABC analysis is simple and practical cost-based, many companies continue to use it. The annual usage value based on historical data determines the performance of ABC Classification. It works well in a relatively stable demand environment. However, its ability to depict operational risk in a perishable product environment is limited by a single-criteria structure. Keshavarz Ghorabaee *et al.* [6] proposed an EDAS-based approach that incorporates multiple criteria. In contrast, Selvaraju and Murugesan [7] used Particle Swarm Optimization to improve ABC classification performance. According to Ravinder and Misra [8], items that are operationally important but low-cost can be misclassified in traditional ABC systems. Additionally, Pal [9] found that static classification often does not align with real-time warehouse requirements.

Various extensions of ABC analysis based on different criteria have been proposed to address these weaknesses. Flores and Whybark [10] combined operational and cost attributes, while Ramanathan [11] used a weighted optimization model to form different criteria categories. Approaches such as FAHP-DEA and fuzzy by Hadi-Vencheh and Mohamadghasemi [12] and similarity-based ranking models by Mallick *et al.* [13] have contributed to new advancements. Although these methods improve the accuracy and robustness of classification, they require pre-assigned weights and criteria, as well as a relatively stable decision environment. They provide little insight into how decision-makers informally adjust the importance of criteria when operational disruptions occur.

Alongside this, the enhancement of digital systems helps in inventory planning. In Harwood [14], the integration of ERP for enterprise-level coordination is discussed. In contrast, Carbonneau et al. [15] discuss the capability of machine learning to improve demand forecast accuracy. However, earlier research by Akkermans *et al.* [16] revealed that ERP systems often face issues with slow information and limited cross-functional response. On the other hand, Singh *et al.* [17] explored Industry 4.0 monitoring technologies face challenges in integration even though they can improve operational visibility. These technologies increases data availability, but it is still more focused on system optimization than on understanding how practitioners interpret and determine inventory priorities in dynamic production conditions.

Overall, technology-based inventory classification and optimization models are becoming increasingly advanced. However, there is little practical evidence on how to apply inventory priorities in perishable food manufacturing environments, especially in cases where cost-based systems cannot directly meet operational requirements. In situations where there is uncertainty and the risk of product deterioration, most studies focus more on model development and less on the decision-making logic of practitioners [9], [18].

Therefore, this study uses a qualitative exploratory approach to examine how practitioners in the Malaysian food manufacturing industry set inventory priorities under conditions of uncertain demand and constraints caused by the perishable nature of the products. Malaysia was chosen as a suitable empirical context due to its growing food manufacturing sector and seasonal demand patterns influenced by festivals and cultural elements. This study contributes to inventory management theory and provides a foundation for developing an adaptive classification system that better reflects the dynamic nature of the perishable food manufacturing environment by identifying the operational logic underlying empirical inventory prioritization.

2. Methodology

2.1 Research Design

The qualitative exploratory research method was used for this study to determine how inventory priorities are established within perishable food products manufacturing operations where the use of cost-based ABC classification does not accurately represent operational requirements. A qualitative research methodology was chosen because inventory decisions are both context-dependent and dynamic in perishable production environments; thus, variability exists in terms of product demand, production processes, and the time-sensitive nature of these production systems; therefore, qualitative methods were selected over static methodologies that rely on pre-established assumptions. The purpose of this study was to inductively describe practitioners' operational decision-making and decision-logic as they establish inventory priorities during periods of uncertainty.

2.2 Data Collection

Data collection was achieved using semi-structured interviews with people who were involved in inventory-related decision making in Malaysian food manufacturing businesses. The three companies chosen represented different sub-segments of food manufacturing and each was involved with perishable inputs and raw materials, time-sensitive manufacturing processes, and volatile customer demand. Each organization also had personnel involved in production planning, purchasing, warehouse management and supply chain management, which enabled the study to obtain evidence of the practices used by those at an operational level when making decisions about inventory.

Table 1
Semi-structured interview company's characteristics

Participant	Company Size / Operational Scale	Automated systems used
A	Large-scale food manufacturer with multi-site operations and high SKU complexity	Custom ERP system, barcode scanning (limited), no RFID/sensors
B	Large-scale food manufacturer with enterprise-level ERP adoption and high operational complexity	SAP ERP, barcode scanning, temperature sensors, limited RFID pilot
C	Large-scale food manufacturer with integrated ERP systems and complex inventory operations	Microsoft Dynamics 365 ERP, handheld barcode scanners, IoT temperature sensors

Note:
Company size is classified based on operational scale and inventory complexity rather than workforce size or financial indicators.

Each interview was conducted as a one-off meeting, lasting around 45-60 minutes, using an interview schedule developed to determine how inventory priorities were established, revised, and cancelled due to variations in customer demand and disruptions to operations. All interviews were recorded on audio tape with the permission of the participants and then transcribed into written format for subsequent analysis. The key characteristics of the participant organizations are shown in Table 1, such as organizational size, the complexity of the inventories held and the degree of use of digital/automated systems.

2.3 Data Analysis

Interview data was analyzed for recurring patterns of meaning across the participating organizations through thematic analysis. The thematic analysis was conducted using an inductive coding technique as defined by Nowell *et al.,* [19], with the six-step procedure as follows; (1) coding, (2) familiarization, (3) generating initial codes, (4) sorting codes, (5) searching for themes and (6) defining and naming themes. Initial codes derived from the interviews were further developed through a process of iterative refinement based upon comparisons of all the interview transcripts. Higher order themes were developed to capture common operational problems and inventory prioritization techniques amongst the participants.

Three major dimensions were identified for the analysis: (i) the volatility of inventory criticality due to the unpredictability of customer demand, (ii) the impact of process embedded and perishable item driven risk on inventory decision making and (iii) the use of experiential multi-criteria judgmental processes where formal classification systems do not provide adequate direction.

2.4 Research Rigor and Trustworthiness

Several methodological techniques were used to increase the rigor and credibility of qualitative data findings. The first methodological strategy was the use of cross-case analysis to provide validation of themes based upon the consistency of theme occurrence within different organizational settings. The second technique to ensure dependability was that the same coding criteria were applied consistently to all data throughout the analytical process. A third methodological strategy was to maintain transparency through reliance on practitioner accounts as empirical evidence to ground all interpretation and, where appropriate, to utilize selected verbatim quotes to support analytical claims regarding key findings.

3. Findings and Discussion

3.1 Theme 1: Temporal Instability of Inventory Criticality

Inventory criticality in food manufacturing is temporal and changes according to how much demand fluctuates and how many times operational issues occur. Practitioners stated that an ABC classification, which relies upon costs being stable for extended periods of time, was often rendered obsolete within short times as operational conditions changed. In fact, seasonal fluctuations in demand are so severe that products previously considered low priority are sometimes given top priority due to the need to maintain production or meet immediate customer demands. Practitioners have been known to temporarily reverse the priority of products classified as A-B-C when the need arises, although the reasons behind the reversal were rarely documented in the system used to classify them. Instead, the changes in product priority are determined by situational awareness and by manual input into the classification system.

Additionally, forecasting has contributed to the variability in inventory criticality because planners use past data to make projections about future demand. However, past data does not always accurately predict how much demand will increase during certain periods of the year.

Therefore, theme one shows that ABC analysis can never be a reliable method for identifying inventory criticality when there are extreme fluctuations in demand.

3.2 Theme 2: Process-Embedded and Perishability-Driven Inventory Risk

Theme two identifies inventory risk in the food manufacturing industry as being primarily process embedded and perishability related. Practitioners identified low-cost products as having higher operational risk if the products were closely tied to specific production processes or had no alternative source of supply. In some cases, the lack of availability of low-cost products is enough to shut down production regardless of the product's limited monetary value.

Perishability increases inventory risk even more significantly due to the time-sensitive nature of the inventory. Practitioners identified that inventory risk is further exacerbated by the shelf life of the products, the degradation of quality over time, and the sensitivity of products to temperature. Practitioners identified that inventory levels may not always mitigate inventory risk. As inventory levels increase, the probability of spoilage, quality rejection, and the failure to meet food safety regulations increases as well. Cold-chain inventory is particularly constrained due to limited storage space and strict handling procedures.

Issuance practices, such as First Expired-First Out (FEFO), are used by practitioners for managing perishable inventory but it has been shown that FEFO on its own, is ineffective for supporting inventory prioritization without access to current, accurate tracking information and up-to-date information related to inventory. As a result, when these conditions do not exist inventory decision-making will revert back to manual inventory checks and based upon practitioner’s past experiences. Thus, theme 2 indicates that traditional cost-based ABC analysis is ineffective in capturing the critical process- and perishability-driven risk dimensions that affect inventory prioritization in food manufacturing.

3.3 Theme 3: Tacit Multi-Criteria Decision Architecture in Practice

Theme three indicates that inventory prioritization in the food manufacturing environment is managed by an informal, experience-based multicriteria decision making framework rather than by a formalized multicriteria decision making model. While structured multicriteria decision making models were not formally implemented in the companies studied, the practitioners interviewed indicated that they make inventory decisions based upon a set of operational criteria, including shelf life, production dependence, demand volatility, lead time reliability, storage constraints, and supplier performance. The relative weightings assigned to each criterion vary by company and by situation. Practitioners adjust the weighting of each criterion as needed in response to changing operational risks. During crisis situations, inventory decisions are often made rapidly and rely on the practitioner's personal experience and judgment. Cost was typically the least crucial factor in making inventory decisions.

While the ability to make rapid inventory decisions in response to operational disruptions allows for greater flexibility and better response times, it also introduces inconsistencies and reduces transparency. The reliance upon tacit knowledge in making inventory decisions makes it difficult to document, replicate, or transfer knowledge among personnel and departments. Thus, Theme 3 indicates a disconnect between the formalized inventory classification systems and the reality of how inventory decisions are made in practice. This suggests that the primary challenge is formalizing and supporting the existing decision logic that practitioners currently utilize in making inventory decisions rather than developing new decision logic.

3.4 Synthesis of Themes and Implications for Inventory Classification

Overall, all three subjects indicated that the importance of inventory in the production of perishable food is shaped by the interaction of various operational factors rather than just cost value. Uncertainty in certain aspects is caused by demand instability. Sudden changes in customer demand directly led to emergency procurement, rescheduling of production, and reclassification of products that were initially considered non-essential based on static ABC logic. However, instability in priority determination is not entirely explained by changes in demand alone.

The risk of product damage increases when the time for correction becomes increasingly limited, which in turn amplifies the impact of demand shocks on operations. Due to product lifespan limitations, sensitivity to temperature, and declining product quality, decisions become more critical, especially when demand forecasts are inaccurate. Minor mistakes can result in losses because damage or regulatory non-compliance can occur under these conditions. Dependence on the production process magnifies this dynamic. When low-cost goods are inserted into a rigid production sequence or when no substitutes are available, stockouts have a greater impact, regardless of financial value. Operational continuity is more important than cost considerations in such circumstances.

These factors do not work separately; instead, they work together. The dependence on processes limits the system's ability to account for changes, while demand shocks increase the risk of damage under the constraints of perishability. Therefore, the importance of inventory now changes over time and is constantly recalibrated, rather than fixed. Static ABC classification is a weak indicator when it comes to real-time operational risk exposure. An effective inventory classification system for manufacturing perishable materials needs to include mechanisms that indicate dynamic importance as well as formalize practitioners' thinking about the various existing criteria. Figure 1 and Table 2 show the composite decision logic for inventory classification in this context.

Table 2
Synthesis of Themes and Implications for Inventory Classification

Theme	Core Empirical Insight	Implication for ABC Classification
Theme 1: Temporal Instability of Inventory Criticality	Inventory criticality changes rapidly due to demand volatility and event-driven disruptions	Static, periodic ABC updates act as lagging indicators and fail to reflect real-time priorities
Theme 2: Process-Embedded and Perishability-Driven Inventory Risk	Inventory risk arises from shelf-life, process dependency, cold-chain constraints, and capacity limitations rather than cost	Cost-based ABC classifications overlook critical operational and quality-related risks
Theme 3: Tacit Multi-Criteria Decision Architecture	Practitioners balance multiple criteria using experience-based judgement under time pressure	Inventory classification systems should formalise multi-criteria reasoning already used in practice

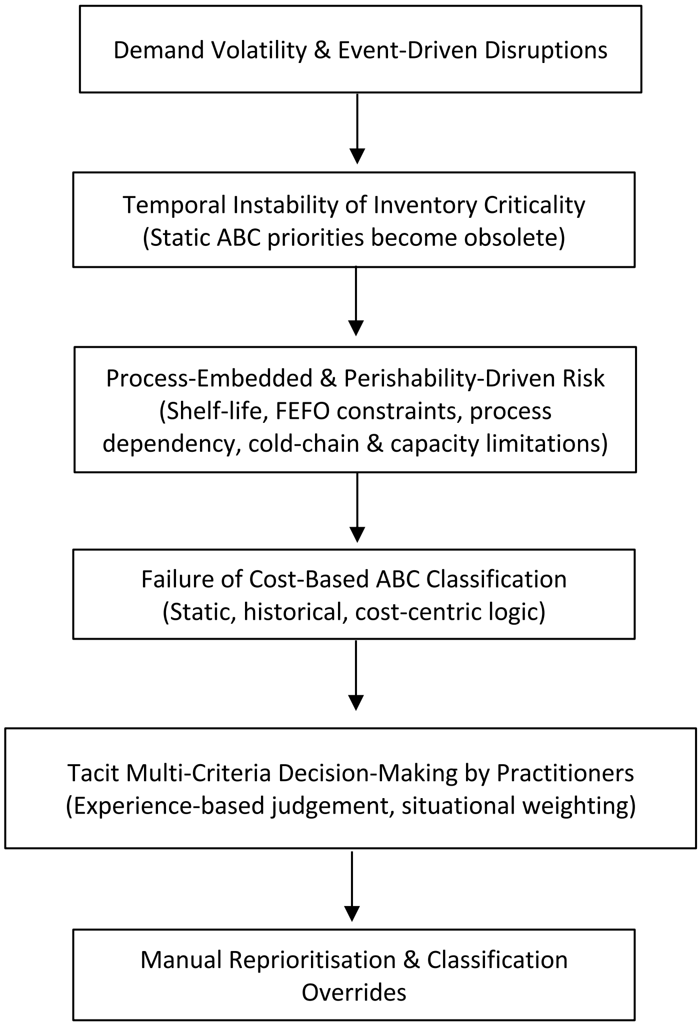


Fig. 1. Practitioner-Based Inventory Prioritisation Logic in Perishable Food Manufacturing

Situation diagnosis, experience-based weighting, and operational validation form a cycle of adaptive prioritization. At the situation diagnosis stage, companies directly assess operational conditions to identify issues and risk exposure. Management experience and knowledge are used to reassess the importance of items beyond their cost. The operational validation stage tests priority adjustments in the actual production environment to ensure that the decisions made are responsive and effective.

This approach differs from optimization-driven multi-criteria frameworks, which typically rely on stable parameter weights. Decision parameters are constantly recalibrated through management feedback, system constraints, and contextual risk signals. The recalibration process that distinguishes this model from conventional inventory classification approaches based on MCDM is the assumption that criteria weights are structurally fixed and do not change according to context. The inductive basis of this model sets it apart from optimization-based Multi-Criteria Decision Making (MCDM) frameworks, which assume that weight structures are stable and independent of conditions.

4. Conclusion and Implications

This study demonstrates that cost-based ABC classification fails to capture dynamic operational risk in perishable food manufacturing environments. Due to operational instability, perishability constraints, and process dependencies, priority determination becomes a coordination effort shaped by organizational routines and practitioner judgement. Traditional cost-based ABC systems still function as a structural reference, but they are insufficient for making operational decisions in an environment full of uncertainty and time sensitivity. Inventory criticality is a dynamic characteristic that is not set based on historical usage value. Instead, it evolves over time in response to disruptions and system constraints. This study provides empirical evidence that multi-criteria decision-making already operates informally in practice. Rather than proposing a purely optimization-driven model, this study emphasizes the importance of formalizing and technologically supporting the adaptive reasoning patterns that are already embedded in organizational practice.

4.1 Practical Implications

ABC classification should be adapted to the company as a basic reference resource rather than an absolute control system. The transition from a static ABC method can be initiated with a structured reclassification cycle supported by operational performance indicators such as demand variation, loss rates, supplier reliability, and process dependency metrics. Classification decisions are more aligned with real-time operating conditions with the help of cross-functional review mechanisms involving production, procurement, logistics, and quality assurance aspects. In the future, semi-automatic adjustment protocols can be integrated into enterprise systems to allow constant reprioritization without completely reducing management oversight. Over-reliance on tacit knowledge will decrease with this integration while maintaining contextual flexibility.

4.2 Theoretical Implications

This study provides empirical support for current theoretical criticisms of traditional cost-based ABC methods for volatile and perishable food manufacturing systems where static classifications fail to effectively evaluate dynamic operational risk. Current theoretical studies suggest multi-criteria and optimization-based classification methods for inventory; however, this study illustrates that multi-criteria decision making already exists in practice; albeit informally and in an experientially driven manner. Since this qualitative exploratory study focuses on identifying how practitioners establish inventory priorities in their work, rather than creating pre-determined theoretical frameworks, the study allows for decision patterns to be inductively developed from the data. Thematic synthesis established a conceptual model of practitioner decision-making with supporting tables and diagrams that do not provide a prescription for application. Therefore, developing a formal conceptual framework based on the findings of this study represents an area for future research.

4.3 Limitations and Future Research

Several obstacles disrupted this study. The findings may be influenced by interview bias arising from retrospective rationalization and social desirability effects. In addition, the qualitative scope and the number of case organizations are limited. The ability to independently verify behavior is limited when relying on self-reported practices. Furthermore, the certification and regulatory conditions in Malaysia's food manufacturing industry may influence preference behavior in ways that differ from less regulated sectors.

Future studies could quantitatively assess the effects of demand fluctuations and the vulnerability risks identified in this study by creating a composite operational risk index. Long-term research has the potential to examine how adaptive prioritization routines evolve alongside the use of real-time monitoring systems and increased digital integration. Experimental comparisons could be conducted between expert-controlled reclassification protocols and semi-automatic protocols to evaluate their impact on performance under volatile demand conditions.

Acknowledgement

This research was not funded by any grant.

References

[1] Ding, Jingying, and Zhenkang Peng. "Heuristics for perishable inventory systems under mixture issuance policies." Omega 126 (2024): 103078. https://doi.org/10.1016/j.omega.2024.103078
[2] Leithner, Magdalena, and Christian Fikar. "A simulation model to investigate impacts of facilitating quality data within organic fresh food supply chains." Annals of Operations Research 314, no. 2 (2022): 529-550. https://doi.org/10.1007/s10479-019-03455-0
[3] Murala, Dileep Kumar, Komali Siddamshetti, and Mariofanna Milanova. "Leveraging IOT in Supply Chain Sustainability: A Provenance Perspective." Blockchain, IoT, and AI Technologies for Supply Chain Management: Apply Emerging Technologies to Address and Improve Supply Chain Management (2024): 147-176. https://doi.org/10.1007/979-8-8688-0315-4_6
[4] Shanker, Saket, Akhilesh Barve, Kamalakanta Muduli, Anil Kumar, Jose Arturo Garza-Reyes, and Sudhanshu Joshi. "Enhancing resiliency of perishable product supply chains in the context of the COVID-19 outbreak." International Journal of Logistics Research and Applications 25, no. 9 (2022): 1219-1243. https://doi.org/10.1080/13675567.2021.1893671
[5] Shin, Moonsoo, Hwaseop Lee, Kwangyeol Ryu, Yongju Cho, and Young-Jun Son. "A two-phased perishable inventory model for production planning in a food industry." Computers & Industrial Engineering 133 (2019): 175-185. https://doi.org/10.1016/j.cie.2019.05.010
[6] Keshavarz Ghorabaee, Mehdi, Edmundas Kazimieras Zavadskas, Laya Olfat, and Zenonas Turskis. "Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS)." Informatica 26, no. 3 (2015): 435-451. https://doi.org/10.15388/Informatica.2015.57
[7] Selvaraju, Kathirvel, and Punniyamoorthy Murugesan. "ABC analysis using Particle Swarm Optimization and its performance evaluation with other models." Benchmarking: an International Journal 29, no. 5 (2022): 1587-1605. https://doi.org/10.1108/BIJ-11-2020-0594
[8] Ravinder, H., and R. B. Misra. "ABC Analysis for Inventory Management: Bridging the Gap between Research and Classroom." American Journal of Business Education 7, no. 3 (2014): 257–264. https://doi.org/10.19030/ajbe.v7i3.8635
[9] Pal, S. Discussion on ABC Analysis on Order Picking Efficiency in E-Commerce Warehouses. AGPE The Royal Gondwana Research Journal of History, Science, Economic, Political and Social Science, 4 (6), 45–52. 2023.
[10] Flores, Benito E., and D. Clay Whybark. "Implementing multiple criteria ABC analysis." Journal of Operations Management 7, no. 1-2 (1987): 79-85. https://doi.org/10.1016/0272-6963(87)90008-8
[11] Ramanathan, Ramakrishnan. "ABC inventory classification with multiple-criteria using weighted linear optimization." Computers & operations research 33, no. 3 (2006): 695-700. https://doi.org/10.1016/j.cor.2004.07.014
[12] Hadi-Vencheh, A., and Amir Mohamadghasemi. "A fuzzy AHP-DEA approach for multiple criteria ABC inventory classification." Expert Systems with Applications 38, no. 4 (2011): 3346-3352. https://doi.org/10.1016/j.eswa.2010.08.119
[13] Mallick, B., S. Das, B. Sarkar, and S. Das. "Application of the modified similarity-based method for multi-criteria inventory classification." Decision Science Letters 8, no. 4 (2019): 445-470. https://doi.org/10.5267/j.dsl.2019.5.001
[14] Harwood, Stephen. ERP: The implementation cycle. Routledge, 2017. https://doi.org/10.4324/9781315094373

[15] Carbonneau, Real, Kevin Laframboise, and Rustam Vahidov. "Application of machine learning techniques for supply chain demand forecasting." European journal of operational research 184, no. 3 (2008): 1140-1154. https://doi.org/10.1016/j.ejor.2006.12.004

[16] Akkermans, Henk A., Paul Bogerd, Enver Yücesan, and Luk N. Van Wassenhove. "The impact of ERP on supply chain management: Exploratory findings from a European Delphi study." European Journal of operational research 146, no. 2 (2003): 284-301. https://doi.org/10.1016/S0377-2217(02)00550-7

[17] Singh, Jagmeet, Amandeep Singh, Harwinder Singh, and Philippe Doyon-Poulin. "Implementation and evaluation of a smart machine monitoring system under industry 4.0 concept." Journal of Industrial Information Integration 43 (2025): 100746. https://doi.org/10.1016/j.jii.2024.100746

[18] Aishwarya, V. M., Banu Yetkin Ekren, Tej Singh, and Vedant Singh. "A stakeholder-centric fuzzy AHP-TOPSIS framework for prioritizing challenges and solutions in the sustainable circular supply chain of electric vehicle batteries." Cleaner Logistics and Supply Chain (2025): 100272. https://doi.org/10.1016/j.clscn.2025.100272

[19] Nowell, Lorelli S., Jill M. Norris, Deborah E. White, and Nancy J. Moules. "Thematic analysis: Striving to meet the trustworthiness criteria." International journal of qualitative methods 16, no. 1 (2017): 1609406917733847. https://doi.org/10.1177/1609406917733847