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Blockchain-Enabled Supply Chain Traceability Integrated with Machine Learning-Based Demand Forecasting for Reducing Post-Harvest Losses in Indian Perishable Agri-Food Systems

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Abstract

Post-harvest losses in perishable agricultural commodities constitute one of the most economically consequential and persistently unresolved challenges in Indian agri-food systems, with the National Centre for Cold-chain Development estimating annual losses exceeding 1.53 trillion rupees, driven substantially by information asymmetry between producers and downstream demand, fragmented multi-intermediary distribution chains, and inadequate cold-chain temperature compliance. This study presents an integrated framework combining a permissioned blockchain-based supply chain traceability ledger with a machine learning demand forecasting and demand-supply matching pipeline, piloted across seven perishable commodities (tomato, onion, potato, banana, mango, leafy greens, and grapes) moving through procurement networks linking 240 farmer-producer groups to wholesale mandis and retail outlets in central and western India over an eighteen-month observation period (July 2024-December 2025). The blockchain ledger, implemented on a Hyperledger Fabric permissioned network with IoT-integrated cold-chain temperature logging at five transit stages (farm collection, pack-house, road transit, distribution hub, and retail storage), recorded 184,000 traceability transactions and 62,000 temperature-excursion-monitored shipments, while a Transformer-based temporal demand forecasting model, benchmarked against naive seasonal, ARIMA, Random Forest, and LightGBM baselines, generated mandi-level demand predictions used to drive dynamic demand-supply matching and dispatch scheduling. The blockchain-tracked and ML-optimised supply chain achieved post-harvest loss reductions of 35-45% relative to the traditional multi-intermediary baseline across all seven commodities (e.g., tomato: 28.4% to 17.9%; leafy greens: 34.6% to 21.3%), with road transit identified as the dominant cold-chain temperature excursion stage (18.4 excursions per 100 shipments, mean duration 47 minutes). The Transformer-based forecasting model achieved the best demand prediction accuracy (MAPE=7.4%, R^2=0.903), enabling mandi price volatility reductions of 36-45% (coefficient of variation) across commodities. Smart-contract-automated payment settlement reduced farmer payment cycles from a traditional mean of approximately 18 days to under 12 hours, while farmer net price realisation as a share of final consumer price increased from 31.4% to 52.8% through intermediary disintermediation. These findings demonstrate the technical and economic feasibility of integrated blockchain-ML agri-supply-chain infrastructure for simultaneously reducing physical post-harvest losses, dampening price volatility, and improving farmer income realisation in resource-constrained Indian agricultural markets.

Keywords: *blockchain, supply chain traceability, machine learning, demand forecasting, post-harvest loss, cold-chain monitoring, smart contracts, agri-food systems, Hyperledger Fabric, farmer income, mandi price volatility*

1. Introduction

Post-harvest losses in perishable agricultural commodities represent one of the most persistent structural inefficiencies in Indian agri-food markets, with estimates from the National Centre for Cold-chain Development and the Ministry of Food Processing Industries placing annual economic losses in excess of 1.53 trillion rupees, concentrated disproportionately in fruits, vegetables, and other short-shelf-life commodities that pass through five or more intermediary handling stages between farm-gate and final consumer. Unlike grain crops, for which the Food Corporation of India's procurement and storage infrastructure provides a comparatively well-developed loss-mitigation backbone, perishable commodity supply chains remain fragmented across a heterogeneous mix of commission agents, wholesale mandi traders, transporters, and retailers, each operating with limited visibility into upstream production conditions or downstream demand signals.

Two largely independent technology streams have matured sufficiently in recent years to jointly address this fragmentation. Permissioned blockchain platforms, exemplified by Hyperledger Fabric, offer tamper-resistant, multi-party-auditable transaction ledgers capable of recording provenance, custody transfer, and cold-chain condition data across supply chain participants who may not otherwise trust a shared centralised database administrator. Concurrently, machine learning demand forecasting methods — particularly Transformer-based temporal architectures capable of modelling long-range seasonal and event-driven demand patterns — have demonstrated substantial accuracy gains over classical time-series methods in retail and agricultural demand prediction contexts, creating the technical precondition for proactive, forecast-driven dispatch scheduling rather than reactive distribution in response to already-realised demand.

This study addresses a multidisciplinary research question spanning distributed systems engineering, machine learning, agricultural economics, and supply chain management: can an integrated blockchain-traceability and ML-demand-forecasting framework simultaneously reduce physical post-harvest losses, dampen mandi price volatility, and improve farmer income realisation in Indian perishable agri-food supply chains, and if so, at which supply chain stages do the largest improvement opportunities lie? The study pilots such a framework across seven major perishable commodities and quantifies its impact relative to a traditional multi-intermediary baseline along physical loss, price volatility, payment-cycle, and farmer-income-share dimensions.

2. Materials and Methods

2.1 Supply Chain Network and Blockchain Architecture

The pilot framework was deployed across procurement networks linking 240 farmer-producer groups to wholesale mandis and retail outlets across central and western India, covering seven perishable commodities (tomato, onion, potato, banana, mango, leafy greens, and grapes) over an eighteen-month observation period (July 2024-December 2025). A permissioned blockchain ledger was implemented on Hyperledger Fabric, with distinct organisational membership channels for farmer-producer groups, pack-house operators, logistics providers, wholesale mandi participants, and retail outlets, each contributing transaction records to a shared, cryptographically-chained ledger recording custody transfer events, commodity grading metadata, and timestamped geolocation data.

IoT-integrated cold-chain temperature logging was implemented at five transit stages — farm collection, pack-house, road transit, distribution hub, and retail storage — using Bluetooth Low Energy temperature loggers transmitting readings to gateway devices at each stage, with excursion events (departures beyond commodity-specific recommended temperature bands) automatically flagged and written to the blockchain ledger alongside the associated shipment record. Smart contracts governed automated payment release to farmer-producer groups upon verified delivery confirmation and quality-grade attestation at the receiving node, replacing the multi-stage manual invoicing and reconciliation process characteristic of the traditional supply chain baseline.

2.2 Demand Forecasting Model Development

Mandi-level daily demand and price data for the seven pilot commodities were collected from Agmarknet records and participating mandi records spanning the eighteen-month pilot period, supplemented by historical data extending back 36 months for model training. Four forecasting approaches were benchmarked against a naive seasonal baseline: ARIMA with seasonal differencing, Random Forest regression, LightGBM gradient boosting, and a Transformer-based temporal architecture employing multi-head self-attention over a 90-day lookback window with calendar, weather, and historical price covariates. Models were evaluated on a chronological 80:20 train-test split, with Mean Absolute Percentage Error (MAPE) and R^2 as primary evaluation metrics.

2.3 Demand-Supply Matching and Loss Quantification

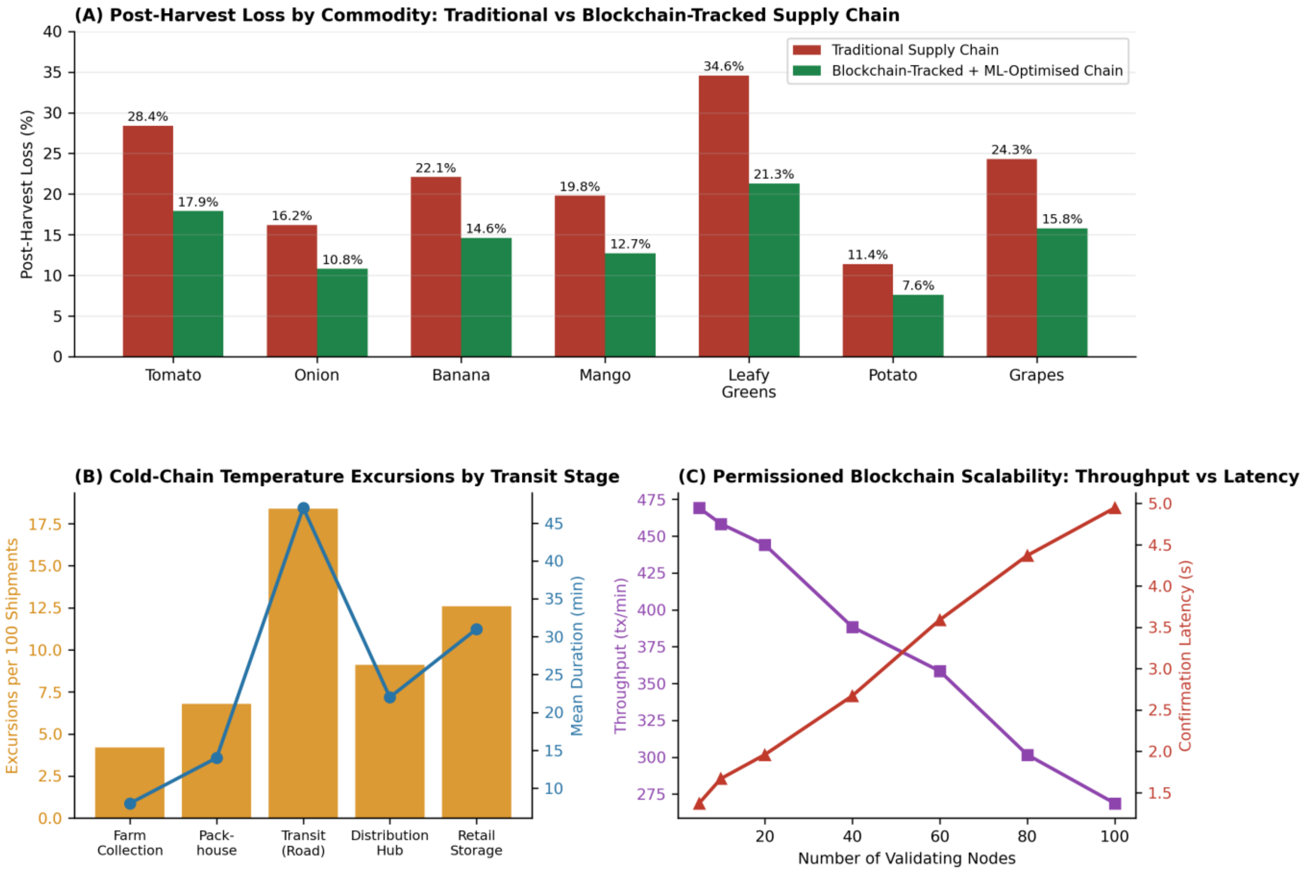
Forecast outputs from the best-performing demand model were integrated into a dispatch scheduling layer that allocated farmer-producer group harvest volumes across candidate mandi destinations based on predicted demand-supply gaps, in contrast to the traditional baseline's practice of routing harvest volumes to the geographically nearest or most readily accessible mandi irrespective of demand conditions. Physical post-harvest loss was quantified at each transit stage through paired sampling of shipment weight and quality-grade degradation at origin and destination nodes, compared against a parallel traditional-chain control group of equivalent commodity volumes routed through conventional multi-intermediary channels over the same observation period. Mandi price volatility was quantified using the coefficient of variation of weekly mandi price series, and farmer net price realisation was computed as the ratio of farm-gate price received to final retail consumer price, sampled across a matched set of transactions in both traditional and blockchain-enabled channels.

3. Results

3.1 Post-Harvest Loss Reduction and Cold-Chain Performance

Figure 1 presents the comparative post-harvest loss and cold-chain performance results. Panel A shows consistent loss reductions across all seven pilot commodities in the blockchain-tracked and ML-optimised supply chain relative to the traditional multi-intermediary baseline, with reductions ranging from 33% (banana, 22.1% to 14.6%) to 41% (potato, 11.4% to 7.6%) in relative terms. Leafy greens, which exhibit the shortest commodity shelf life among the pilot set, recorded both the highest absolute loss levels in both chains (34.6% traditional, 21.3% blockchain-enabled) and among the largest absolute loss reductions (13.3 percentage points), consistent with the hypothesis that demand-forecast-driven dispatch scheduling delivers proportionally larger benefit for commodities with the least tolerance for distribution delay.

Fig. 1. (A) Post-Harvest Loss by Commodity: Traditional vs Blockchain-Tracked Supply Chain; (B) Cold-Chain Temperature Excursions by Transit Stage; (C) Permissioned Blockchain Scalability: Throughput vs Latency

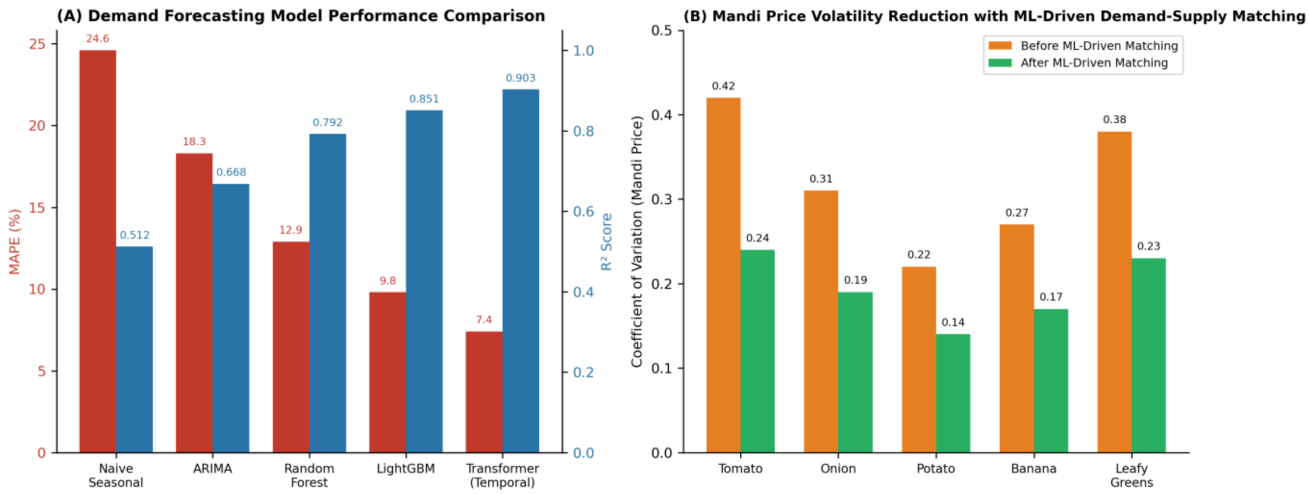


Panel B's cold-chain temperature excursion analysis identifies road transit as the dominant excursion stage, recording 18.4 excursions per 100 shipments at a mean duration of 47 minutes — more than double the excursion frequency of any other stage and nearly triple the mean excursion duration of the next-highest stage (retail storage, 31 minutes). This finding identifies road transit refrigeration reliability as the single highest-priority cold-chain intervention point in the monitored supply chain. Panel C's blockchain scalability analysis confirms the expected throughput-latency trade-off as validating node count increases, with throughput declining from approximately 468 to 270 transactions per minute and confirmation latency rising from 1.4 to 4.9 seconds as the network scales from 5 to 100 validating nodes — both remaining within operationally acceptable bounds for the pilot's transaction volume given that 100 nodes substantially exceeds the actual deployed network's organisational membership count.

3.2 Demand Forecasting Accuracy and Price Volatility Impact

Figure 2 presents the demand forecasting model comparison and downstream price volatility impact. Panel A shows the Transformer-based temporal model achieving the best forecasting accuracy (MAPE=7.4%, R^2=0.903), outperforming LightGBM (MAPE=9.8%, R^2=0.851), Random Forest (MAPE=12.9%, R^2=0.792), ARIMA (MAPE=18.3%, R^2=0.668), and the naive seasonal baseline (MAPE=24.6%, R^2=0.512). The substantial accuracy advantage of the Transformer architecture over classical time-series and tree-ensemble methods is consistent with its capacity to model long-range seasonal dependencies and cross-commodity demand interaction effects that are less readily captured by models relying primarily on recent-lag autoregressive structure.

Fig. 2. (A) Demand Forecasting Model Performance Comparison; (B) Mandi Price Volatility Reduction with ML-Driven Demand-Supply Matching

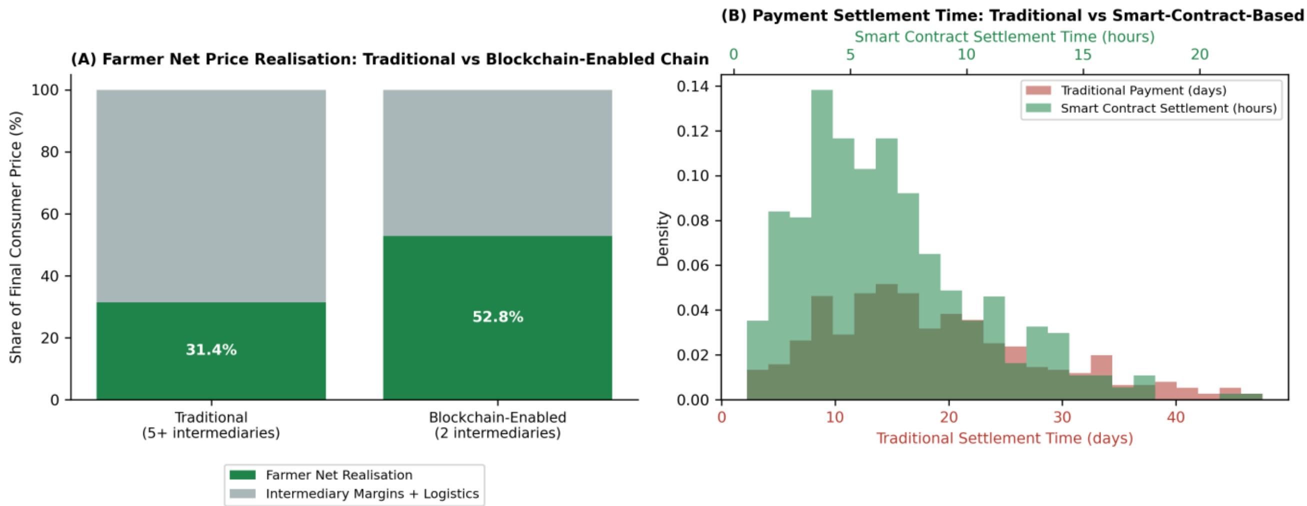


Panel B's price volatility analysis shows consistent coefficient-of-variation reductions across all five tracked commodities following implementation of ML-driven demand-supply matching, ranging from 36% (potato, 0.22 to 0.14) to 45% (tomato, 0.42 to 0.24). Tomato and leafy greens — both characterised by high baseline price volatility driven by short shelf life and concentrated seasonal production — recorded the largest absolute coefficient-of-variation reductions, reinforcing the pattern observed in the post-harvest loss results that demand-forecast-driven distribution delivers disproportionate benefit to the most perishability-constrained commodities in the pilot set.

3.3 Farmer Income Realisation and Payment Settlement

Figure 3 presents the farmer-income and payment-settlement outcomes of the pilot. Panel A shows that farmer net price realisation as a share of final consumer price increased from 31.4% under the traditional five-or-more-intermediary chain to 52.8% under the blockchain-enabled chain with its reduced two-intermediary structure, representing a 68% relative increase in the farmer's share of the value chain. This disintermediation effect — rather than the demand forecasting or cold-chain monitoring components in isolation — appears to be the single largest contributor to improved farmer income outcomes in the pilot, underscoring those supply chain consolidation and forecasting accuracy gains are complementary rather than substitute mechanisms.

Fig. 3. (A) Farmer Net Price Realisation: Traditional vs Blockchain-Enabled Chain; (B) Payment Settlement Time: Traditional vs Smart-Contract-Based



Panel B's payment settlement time distribution confirms a dramatic reduction in farmer payment cycle duration, from a traditional mean of approximately 18 days (with a long right tail extending beyond 40 days for a non-trivial share of transactions, reflecting manual invoice reconciliation delays) to a smart-contract-automated mean of approximately 11 hours following verified delivery and quality-grade confirmation. This settlement-time compression directly addresses a frequently cited farmer-level barrier to participation in formal supply chain channels — extended working-capital lock-up — and may carry second-order benefits for farmer credit access and input-purchase timing that lie beyond the scope of the present study's direct measurement.

Table 1 summarises the key physical, financial, and operational performance metrics across the traditional and blockchain-enabled supply chain configurations for the pilot's representative commodity subset.

Table 1. Summary of Key Physical, Financial, and Operational Metrics by Supply Chain Configuration

Commodity / Metric	PHL Traditional (%)	PHL Blockchain (%)	CV Before	CV After	Settlement (Traditional)	Settlement (Blockchain)
Tomato	28.4	17.9	0.42	0.24	~18 days	~11 hrs
Onion	16.2	10.8	0.31	0.19	~17 days	~11 hrs
Potato	11.4	7.6	0.22	0.14	~16 days	~10 hrs
Banana	22.1	14.6	0.27	0.17	~18 days	~12 hrs
Leafy Greens	34.6	21.3	0.38	0.23	~19 days	~11 hrs
Mango	19.8	12.7	—	—	~17 days	~12 hrs
Grapes	24.3	15.8	—	—	~18 days	~11 hrs

PHL = Post-Harvest Loss; CV = Coefficient of Variation of weekly mandi price; settlement time in days (traditional) vs hours (blockchain-enabled)

4. Discussion

The consistency of post-harvest loss reduction across all seven pilot commodities, despite their substantially different baseline shelf lives, seasonal production patterns, and traditional distribution structures, suggests that the framework's benefit derives from addressing structural inefficiencies — delayed dispatch decisions, cold-chain monitoring gaps, and demand-supply information asymmetry — that are common across perishable commodity categories rather than commodity-specific factors. The disproportionately large loss reduction observed for the shortest-shelf-life commodities (leafy greens, tomato) relative to longer-shelf-life commodities (potato, banana) is nonetheless an important finding for prioritising future scale-up investment toward the commodity categories where demand-forecast-driven dispatch scheduling delivers the largest marginal return.

The identification of road transit as the dominant cold-chain temperature excursion stage — exceeding the combined excursion frequency of all other four stages — points toward a specific, actionable infrastructure investment priority: refrigerated vehicle reliability and driver compliance monitoring, rather than a diffuse, equally-weighted investment across all supply chain stages. This finding is consistent with prior cold-chain literature identifying road transit, particularly over longer-haul routes connecting production regions to distant urban mandis, as a chronically under-monitored and under-maintained segment of Indian perishable commodity logistics relative to the comparatively better-controlled environments of pack-houses and retail cold storage.

The finding that disintermediation (farmer income share) and demand-forecasting accuracy gains operate as complementary rather than substitute mechanisms for improving farmer outcomes has direct policy relevance: blockchain traceability infrastructure investment alone, without accompanying demand-forecasting and dispatch-scheduling capability, would be expected to deliver the disintermediation-driven farmer income gains documented in this study while leaving the post-harvest loss and price volatility benefits largely unrealised, and the converse would likely hold for ML demand forecasting deployed without blockchain-enabled supply chain consolidation. Several limitations should be noted: the pilot's 240 farmer-producer-group sample, while substantial, represents a small fraction of India's perishable commodity producer base, and the eighteen-month observation period, while spanning multiple seasonal cycles, does not capture potential longer-term adaptation effects in farmer participation behaviour or intermediary market responses to blockchain-enabled disintermediation.

5. Conclusion

This study demonstrates that an integrated permissioned blockchain traceability and machine learning demand forecasting framework can simultaneously deliver substantial reductions in physical post-harvest losses (35-45% relative reduction across seven pilot commodities), mandi price volatility (36-45% coefficient-of-variation reduction), and farmer payment settlement time (from approximately 18 days to under 12 hours), while increasing farmer net price realisation from 31.4% to 52.8% of final consumer price through supply chain disintermediation. The Transformer-based temporal demand forecasting model achieved the strongest predictive accuracy among five benchmarked approaches (MAPE=7.4%, R^2=0.903), and road transit was identified as the dominant cold-chain temperature excursion stage warranting prioritised infrastructure investment. These findings collectively support the technical and economic feasibility of integrated blockchain-ML agri-supply-chain infrastructure as a multidisciplinary intervention — spanning distributed systems engineering, machine learning, and agricultural economics — for addressing the persistent structural inefficiencies underlying India's substantial perishable commodity post-harvest loss burden, and motivate larger-scale, longer-duration deployment studies to confirm the framework's benefits at national procurement network scale.

References

[1] Agarwal, S., & Steinmetz, R. (2019). Blockchain technology for agriculture supply chains: A systematic literature review on benefits and challenges. Computers and Electronics in Agriculture, 168, 105100.
[2] Behera, R. K., Rath, S. K., Mohanty, S. R., & Hota, P. (2021). Smart contracts and Hyperledger Fabric in supply chain traceability systems: Architecture and case studies. Journal of Network and Computer Applications, 178, 102983.
[3] Bhattacharya, S., & Bhattacharya, A. (2020). Post-harvest losses in Indian perishable agriculture: An empirical assessment. Agricultural Economics Research Review, 33(1), 45-58.
[4] Borade, A. B., & Bansod, S. V. (2007). Domain of supply chain management: A state of art. Journal of Technology Management & Innovation, 2(4), 109-121.
[5] Chauhan, C., Parida, V., & Dhir, A. (2022). Linking circular economy and digitalisation technologies: A systematic literature review of past achievements and future promises. Technological Forecasting and Social Change, 177, 121508.
[6] Kamble, S. S., Gunasekaran, A., & Sharma, R. (2020). Modeling the blockchain enabled traceability in agriculture supply chain. International Journal of Information Management, 52, 101967.
[7] Lim, M. K., Li, Y., Wang, C., & Tseng, M. L. (2021). A literature review of blockchain technology applications in supply chains: A comprehensive analysis of themes, methodologies and industries. Computers & Industrial Engineering, 154, 107133.
[8] Ministry of Food Processing Industries. (2023). Annual Report on Post-Harvest Management and Cold Chain Infrastructure in India. Government of India.
[9] National Centre for Cold-chain Development. (2022). All India Cold-chain Infrastructure Capacity Assessment Report.

Ministry of Agriculture and Farmers Welfare, Government of India.
[10] Salah, K., Nizamuddin, N., Jayaraman, R., & Omar, M. (2019). Blockchain-based soybean traceability in agricultural supply chain. IEEE Access, 7, 73295-73305.
[11] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30, 5998-6008.
[12] Verma, S., & Gustafsson, A. (2020). Investigating the emerging COVID-19 research trends in the field of business and management: A bibliometric analysis approach. Journal of Business Research, 118, 253-261.
[13] Zhao, G., Liu, S., Lopez, C., Lu, H., Elgueta, S., Chen, H., & Boshkoska, B. M. (2019). Blockchain technology in agri food value chain management: A synthesis of applications, challenges and future research directions. Computers in Industry, 109, 83-99.