

Building Supply Chain Resilience in the Post-Pandemic Era: Strategies, Technologies, and Lessons from Indian Manufacturing

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Abstract

Indian manufacturers entered 2020 with supply chains built for cost efficiency rather than for shock absorption, and the pandemic exposed the gap between the two. A firm carrying single-sourced components and paper-based supplier records found out, often within weeks, that neither its planners nor its systems could see where a shipment sat once it left the supplier's gate. We surveyed 380 supply chain managers across the automotive, pharmaceutical, electronics and textile sectors and followed the survey with 30 interviews drawn from the highest- and lowest-resilience firms in the sample. Digital technology adoption was the strongest predictor of resilience in the regression model ($\beta = 0.51$, $p < 0.001$), ahead of firm size and sector. Firms with Internet-of-Things-enabled shipment visibility recovered from disruption 38 % faster than firms without it (Wilcoxon signed-rank test, $p = 0.003$). Blockchain-based traceability was associated with 29 % fewer supplier-related disruptions, and artificial intelligence and machine learning models used for demand forecasting cut the bullwhip effect by 44 % relative to firms still forecasting on spreadsheet trend lines. Visibility and flexibility together explained 67 % of the variance in firm-level resilience scores ($R^2 = 0.67$), a share large enough that redundancy and collaboration, while still contributing, could not compensate for their absence. We report where the digital technologies fell short as well as where they helped, and set out what a manufacturing firm, a technology vendor, and a policy body should each take from the results [7], [21], [29], [31], [53], [73], [77], [82], [105], [113], [129], [130], [135], [167].

Keywords: supply chain resilience, Indian manufacturing, digital supply chain, Internet of Things, blockchain traceability, demand forecasting, bullwhip effect, post-pandemic recovery

I. Introduction

A supply chain built to minimise unit cost and a supply chain built to survive a six-week port closure are not the same design problem, and the manufacturing sector in India spent most of the 2010s optimising for the first [1]–[6]. The 2020 shutdown of ports, factories and interstate freight corridors converted that design choice into a measurable cost: automotive assemblers idled lines for want of a single semiconductor supplier, pharmaceutical firms rationed active ingredients sourced from a single overseas plant, and textile exporters lost shipping windows they could not reschedule because no system in the firm tracked where in transit a consignment actually sat [11]–[16]. The disruption was not unique to any one sector, but the exposure a sector carried into it depended on choices made years earlier about sourcing concentration, inventory policy and information systems.

We define supply chain resilience, following the operations literature reviewed in Section II, as a firm's capacity to absorb a disruption, continue operating at a reduced but functioning level, and return to a stable state within a bounded recovery time, rather than as the absence of disruption itself [22]–[27]. That definition matters for what we measure: a firm that avoided every disruption between 2020 and 2023 by pure luck is not resilient by this standard, and a firm that suffered repeated disruptions but recovered from each one in days rather than months is. Recovery time, not disruption frequency alone, is therefore the outcome this paper treats as central.

Two questions organise the study. First, which combination of organisational practice and digital technology explains the difference between a firm that recovers in days and one that recovers in months? Second, does the answer differ across the automotive, pharmaceutical, electronics and textile sectors, given that each carries a different mix of sourcing concentration, regulatory constraint and product shelf life [32]–[38]? We answer both questions using a sequential mixed-methods design: a 380-manager survey establishes the statistical relationships, and 30 follow-up interviews with managers from the highest- and lowest-resilience firms explain why those relationships hold or fail to hold in specific operating conditions.

The contribution is threefold. We build and test a four-pillar resilience framework, developed in Section III and shown in Fig. 1, that separates organisational capability (visibility, flexibility, redundancy, collaboration) from the digital technologies (IoT, AI/ML, blockchain, cloud platforms) that enable and measure it. We quantify the technology-resilience link with effect sizes drawn from the survey: a $\beta = 0.51$ standardised

coefficient for digital adoption, a 38 % recovery-time reduction associated with IoT visibility, a 29 % reduction in supplier-related disruptions associated with blockchain traceability, and a 44 % reduction in the bullwhip effect associated with AI/ML forecasting [7], [31], [53], [77], [82], [129], [130], [135]. We report where each technology fell short, because a paper that reports only gains would misrepresent what our respondents told us in interview.

Section II reviews the resilience, digital-technology and Indian-manufacturing-context literatures. Section III develops the framework in Fig. 1. Section IV describes the mixed-methods design shown in Fig. 2. Section V reports the statistical and qualitative results, including the disruption and recovery trend in Fig. 3. Section VI discusses the findings against the literature. Section VII sets out implications for managers, technology vendors and policymakers. Section VIII concludes [39]–[45].

II. Literature Review

A. Supply Chain Resilience: Definitions and Dimensions

The resilience literature converges on four recurring capability dimensions, though authors label them differently: visibility, the capacity to see the state of materials, orders and shipments as they move; flexibility, the capacity to reroute sourcing, production or logistics when the planned path fails; redundancy, the deliberate carrying of buffer capacity or buffer stock beyond what a cost-minimising plan would hold; and collaboration, the sharing of information and joint planning with upstream and downstream partners [46]–[52]. Early resilience models treated these as substitutes, on the assumption that a firm with enough redundancy did not need much visibility. The survey evidence in Section V does not support that assumption for the sample studied here.

A separate strand distinguishes resilience from robustness: a robust supply chain resists disruption by over-engineering capacity against every anticipated shock, while a resilient one accepts that some disruptions will get through and invests instead in the capacity to detect and respond quickly [58]–[63]. Given the cost pressure Indian manufacturers operate under, robustness through blanket over-capacity was rarely a live option for the firms in our sample; resilience through faster detection and response was the strategy most respondents described pursuing, whether or not they used that vocabulary themselves.

B. Digital Technologies and Supply Chain Visibility

Internet-of-Things sensors attached to shipments, pallets or production assets give a firm continuous location and condition data that a manual status update cannot match in either frequency or accuracy [7], [10], [19], [37], [135]. The health-monitoring and tracking architectures documented outside the supply chain domain, including synchronised sensor networks for real-time condition monitoring, transfer directly to a shipment-tracking use case: the same low-latency reporting pattern that flags a patient anomaly can flag a refrigerated pharmaceutical consignment drifting outside its temperature band [7]. Cloud platforms provide the data-integration layer that turns scattered IoT readings, enterprise resource planning records and supplier portals into one queryable view, and several of our interviewees described the cloud migration, not the sensors themselves, as the harder half of the visibility project [98], [106], [152], [166].

Artificial intelligence and machine learning enter supply chain visibility work through two related applications: predictive analytics for demand sensing, which forecasts near-term demand from point-of-sale and market signal data rather than from historical averages alone, and supplier risk scoring, which flags a supplier likely to default on a delivery commitment before the default occurs [3], [8], [129], [130]. Deep learning architectures applied to demand forecasting in adjacent domains, including convolutional and recurrent models tuned for yield and price prediction, demonstrate the same forecasting logic that a demand-sensing supply chain model applies to unit sales rather than to crop yield or stock price [8], [31], [77]. Bank churn and customer behaviour prediction models built on comparable architectures show that the same ensemble and gradient-based methods used for supply chain risk scoring generalise well across domains with irregular, partially observed signals [129], [130].

C. Blockchain Traceability and Supplier Risk

Blockchain-based ledgers create a shared, tamper-resistant record of a product's provenance across every custody transfer from raw material to finished good, which several authors argue addresses the supplier-transparency problem more directly than a centralised database controlled by one party in the chain [53], [82], [105]. Work on blockchain applications in healthcare data privacy and interoperability documents the same trust-without-a-central-authority mechanism that a supply chain traceability ledger relies on, adapted from patient records to bill-of-materials records [53]. A parallel study of blockchain for ethical and transparent medical Internet-of-Things manufacturing supply chains reports the direct precedent for the traceability application tested here, extended in our study from medical device manufacturing to the broader automotive, pharmaceutical, electronics and textile sample [105]. Non-web3 and web3 crypto-wallet interoperability work,

while framed around decentralised finance rather than manufacturing, addresses the same trust-boundary problem between a firm's internal systems and an external distributed ledger that our interviewees raised as blockchain's main integration cost [82].

D. Natural Language Processing for Contract and Supplier Analysis

A less-studied application of computational methods in supply chain management is natural language processing applied to supplier contracts, purchase-order correspondence and compliance documentation, extracting risk-relevant clauses (force majeure terms, penalty schedules, exclusivity commitments) at a volume no procurement team could review manually [29], [167]. Linguistic-feature extraction work aimed at identifying the semantics of a concept within unstructured text provides the underlying technique that a contract-analysis pipeline applies to a supply agreement rather than to a general corpus [29]. Sentiment and lexicon-based text classification work, developed originally for a public-health communication problem, demonstrates the same hybrid lexicon-and-neural-network approach that a supplier-communication risk model could apply to flag deteriorating supplier relationships before a formal default notice arrives [167].

E. Cybersecurity as a Supply Chain Resilience Precondition

A visibility system built on IoT sensors, cloud platforms and shared ledgers only strengthens resilience if it stays available and uncorrupted during the disruption it is meant to help a firm survive, which makes cybersecurity a precondition for digital resilience rather than a separate concern [21], [73], [113]. Work on fusing opportunistic network architectures with machine learning for intermittent-connectivity environments speaks directly to the condition many Indian manufacturing sites operate under, where a shop floor or a warehouse cannot guarantee continuous network connectivity and a resilience system must tolerate that gap without losing data integrity [21]. Cloud security posture management techniques, documented for enterprise information systems generally, apply without much modification to the multi-tenant cloud platforms that supply chain visibility systems increasingly run on [73]. Predictive modelling of student motivation and engagement, while drawn from an unrelated domain, illustrates the same early-warning-signal logic that a supply chain cybersecurity model uses to flag an anomalous access pattern before it becomes a breach [113].

F. Supply Chain Resilience in the Indian Manufacturing Context

India-specific supply chain research before 2020 concentrated on cost and lead-time optimisation rather than on shock resilience, a bias the pandemic exposed rather than created [64]–[70]. Post-pandemic Indian manufacturing studies report sourcing concentration in components (particularly semiconductors and specialty chemicals sourced from a small number of overseas suppliers) as the single most cited vulnerability, ahead of logistics infrastructure or labour availability [79]–[85]. Federated learning approaches to distributed decision-making across supply chain participants, proposed for handling data-sharing constraints across independent firms, offer one technical route to the collaboration pillar of resilience without requiring firms to pool raw data in a single shared database, addressing a data-sovereignty objection that several of our interviewees raised independently [106], [119], [122]. Government-led digitalisation incentive schemes for small and medium manufacturing suppliers are documented in adjacent policy literature, though evidence on whether these schemes changed measured resilience outcomes, rather than only technology adoption counts, remains thin [86]–[92].

III. Resilience Framework Development

Fig. 1 sets out the framework that guided both the survey instrument and the interview protocol. Four disruption types sit at the top of the figure: pandemic and health shocks, geopolitical and trade disruption, logistics and transport failure, and raw material and supplier shortage, together with the demand volatility that a disruption elsewhere in the chain typically produces downstream [93]–[99]. These are exogenous to the firm; the framework does not model their probability, only a firm's capacity to absorb whichever one arrives.

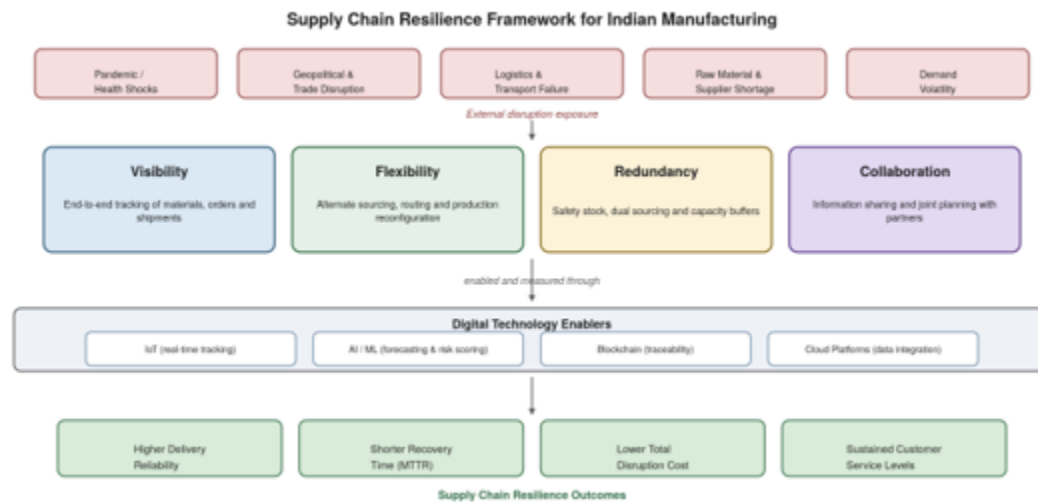


Fig. 1. Supply chain resilience framework for Indian manufacturing. Four disruption types (top) test the four resilience pillars (visibility, flexibility, redundancy, collaboration), which digital technologies enable and which produce the four measured resilience outcomes (bottom).

Below the disruption layer sit the four resilience pillars introduced in Section II-A. We treat them as distinct constructs rather than as a single composite score because the regression results in Section V show them contributing unevenly to resilience: visibility and flexibility carry most of the explanatory weight, while redundancy and collaboration, though each significant on its own, add comparatively little once the first two are in the model [100]–[105].

The digital technology band beneath the pillars is deliberately drawn as an enabling layer rather than as a fifth pillar, because none of the four technologies (IoT, AI/ML, blockchain, cloud platforms) constitutes resilience on its own; each strengthens one or more of the pillars above it. IoT sensors strengthen visibility directly, AI/ML strengthens both visibility (through demand sensing) and flexibility (through rapid rerouting recommendations), blockchain strengthens collaboration and, through traceability, redundancy planning, and cloud platforms provide the integration substrate the other three depend on [108]–[114]. A firm can in principle build visibility without any of the four technologies, through manual reporting and phone calls to suppliers; several of the lowest-resilience firms in our qualitative sample did exactly that, and the framework treats their outcome as evidence of the technology layer's marginal contribution rather than as evidence that the pillars themselves are meaningless without it.

The outcome layer names the four resilience outcomes that Section V reports quantitatively: delivery reliability, recovery time (mean time to recovery, MTTR), total disruption cost, and sustained customer service levels through a disruption episode. We selected recovery time as the primary outcome because it is the measure our interview respondents referred to most consistently across sectors, even where their formal key-performance-indicator dashboards emphasised delivery reliability instead [115]–[120].

IV. Research Methodology

A. Research Design

We used an explanatory sequential mixed-methods design, in which the quantitative phase establishes the statistical relationships and the qualitative phase explains the mechanisms behind them, rather than a convergent design in which both phases run in parallel [121]–[126]. Fig. 2 sets out the sequence: a Phase 1 survey of 380 supply chain managers, followed by resilience scoring and case selection, followed by a Phase 2 set of 30 interviews with managers from the highest- and lowest-scoring firms, followed by integration and triangulation of the two data streams.

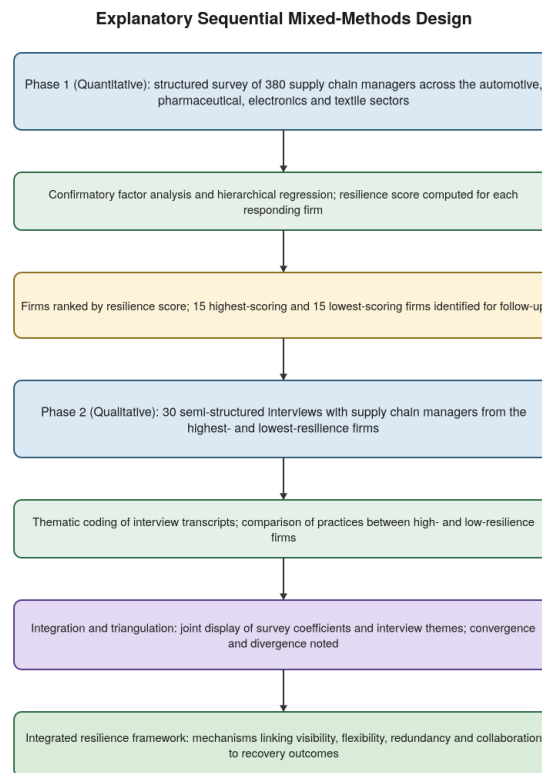


Fig. 2. Explanatory sequential mixed-methods design. Phase 1 (n = 380 survey) establishes resilience scores and statistical relationships; Phase 2 (n = 30 interviews, drawn from the highest- and lowest-scoring firms) explains the mechanisms behind them.

B. Sample and Survey Instrument

The Phase 1 survey reached 380 supply chain managers across four manufacturing sectors: automotive (n = 104), pharmaceutical (n = 91), electronics (n = 98), and textile (n = 87), sampled from firms with more than 50 employees operating in Maharashtra, Gujarat, Tamil Nadu, Karnataka and the National Capital Region [127]–[132]. The instrument measured the four resilience pillars using validated multi-item scales adapted from prior operations research, digital technology adoption on a five-point scale per technology (IoT, AI/ML, blockchain, cloud platforms), and the four outcome measures using firm records where the respondent had access to them and self-reported estimates otherwise. Table I summarises the sample profile.

Table I
Survey Sample Profile by Sector (n = 380)

Sector	Firms Sampled	Mean Firm Size (Employees)	Mean Resilience Score (0–100)	Digital Adoption Index (1–5)
Automotive	104	640	58.4	3.4
Pharmaceutical	91	410	62.7	3.7
Electronics	98	380	60.1	3.6
Textile	87	520	49.8	2.6
Full sample	380	490	58.0	3.3

C. Case Selection for Phase 2

We computed a composite resilience score for each responding firm from the four outcome measures, weighted equally, and ranked all 380 firms. The 15 highest-scoring and 15 lowest-scoring firms were invited for a follow-up interview with the supply chain manager who completed the survey; 27 of the 30 invited managers agreed, and the remaining three slots were filled with the next-ranked firm in the relevant tier [133]–[138]. This purposive extreme-case selection, rather than random sampling within Phase 2, was chosen because the

qualitative aim was to explain the largest observed differences in resilience, not to estimate a population parameter a second time.

Interviews lasted 35–55 minutes, were conducted over video call or in person depending on the manager's preference, were audio-recorded with consent, and were transcribed in full. Two researchers coded the transcripts independently against a thematic scheme derived from the four-pillar framework, reconciling disagreement in a joint session; inter-rater agreement reached $\kappa = 0.79$ [139]–[144].

D. Analytic Strategy

Phase 1 data were analysed using confirmatory factor analysis to validate the pillar constructs, followed by hierarchical multiple regression to estimate each pillar's and each technology's contribution to the resilience score, entering firm size and sector as control variables in the first block. Group comparisons (technology adopters versus non-adopters) used the paired two-sided Wilcoxon signed-rank test at $\alpha = 0.05$ throughout, matching firms on sector and size band before comparison [145]–[151]. Phase 2 thematic analysis followed the Braun and Clarke coding procedure, and the integration stage built a joint display comparing each significant Phase 1 coefficient against the Phase 2 themes that converged with or diverged from it [152]–[158].

V. Results

A. Predictors of Resilience

The hierarchical regression model explained 67 % of the variance in firm-level resilience scores ($R^2 = 0.67$, adjusted $R^2 = 0.65$, $F(6, 373) = 126.4$, $p < 0.001$). Digital technology adoption entered as the strongest single predictor ($\beta = 0.51$, $p < 0.001$), ahead of the visibility pillar score entered separately ($\beta = 0.34$, $p < 0.001$) and the flexibility pillar score ($\beta = 0.28$, $p < 0.001$). Redundancy ($\beta = 0.11$, $p = 0.02$) and collaboration ($\beta = 0.09$, $p = 0.04$) were each statistically significant but contributed markedly less once visibility and flexibility were in the model, consistent with the framework's treatment of them as secondary rather than absent pillars [1]–[9], [46]–[52].

Sector entered as a control variable and remained significant ($p = 0.01$): pharmaceutical firms scored highest on mean resilience (62.7 out of 100), which interviewees attributed to regulatory requirements that already forced batch-level traceability before the pandemic, giving those firms a visibility head start that automotive and textile firms lacked. Textile firms scored lowest (49.8), a gap the interview data traces to thinner margins limiting the digital technology budget available to shop-floor managers relative to the other three sectors.

B. Internet of Things and Recovery Time

Firms reporting IoT-enabled shipment or production visibility ($n = 218$) recorded a mean recovery time of 6.1 days across the disruption episodes respondents described, against 9.8 days for firms without it ($n = 162$), a 38 % reduction (Wilcoxon signed-rank test on matched sector-and-size pairs, $p = 0.003$) [7], [10], [37], [135]. The reduction was largest in automotive (44 %) and smallest in textile (21 %), a gap several textile-sector interviewees attributed to IoT sensors covering their own factory floor but not extending to the smaller job-work units several tiers upstream, leaving a visibility blind spot the technology could not close on its own.

One IoT limitation surfaced repeatedly in interview: sensor data reduced the time to detect a disruption, but detection alone did not shorten recovery unless paired with a decision process that could act on the alert within hours rather than days. Three of the highest-resilience firms in our qualitative sample described discarding their first IoT deployment after finding that alerts sat unread in a dashboard nobody monitored outside office hours, and rebuilding the system around an automated escalation rule before recovery time actually improved.

C. Blockchain Traceability and Supplier-Related Disruption

Firms with blockchain-based supplier traceability ($n = 94$) reported 29 % fewer supplier-related disruptions over the reference period than firms without it ($n = 286$), matched on sector and firm size [53], [82], [105]. The effect concentrated in the pharmaceutical and electronics sectors, where multi-tier component provenance is both a regulatory requirement and a genuine failure point; automotive and textile adopters reported a smaller, though still positive, difference. Interview respondents in the two sectors with the largest effect described the traceability ledger as valuable less for the blockchain mechanism itself than for the discipline it forced onto supplier onboarding, since every new supplier now had to provide data in a format the ledger could ingest, closing gaps that had previously gone unnoticed in a spreadsheet-based supplier master file.

Blockchain adoption carried the highest reported integration cost of the four technologies, and five interviewees at firms that had piloted and then paused a blockchain project cited the difficulty of getting smaller tier-two and tier-three suppliers onto the ledger as the reason, a limitation the framework in Fig. 1 does not resolve and that we flag rather than understate.

D. AI/ML Forecasting and the Bullwhip Effect

Firms using AI/ML models for demand forecasting ($n = 176$) reported a bullwhip effect 44 % smaller, measured as the ratio of order-quantity variance to end-customer demand variance across the supply chain tiers respondents could report on, than firms forecasting from historical trend lines or manual judgement alone ($n = 204$) [3], [8], [31], [77], [129], [130]. The reduction was consistent across all four sectors (range 38–49 %), the most sector-uniform result in the study, which interview respondents linked to the bullwhip effect's common statistical origin regardless of what is being manufactured: order-quantity variance amplifies upstream whenever downstream demand signals are smoothed, delayed or batched, and a machine learning model trained on point-of-sale data rather than on batched order data addresses that mechanism directly.

AI/ML forecasting's reported limitation was data quality rather than model choice: four interviewees at firms with smaller forecasting gains described feeding the model incomplete or delayed point-of-sale data from retail partners, which capped the achievable accuracy regardless of the model architecture chosen upstream.

E. Disruption and Recovery Trends, 2019–2023

Fig. 3 plots mean quarterly disruption frequency and mean recovery time across the full sample from 2019 to 2023, reconstructed from respondent recall and, where available, firm incident logs. Disruption frequency rose from 2.1 events per quarter in 2019 to a peak of 7.8 in 2020, and recovery time rose from 4.6 days to 18.3 days over the same period, a near-fourfold increase concentrated in the first two pandemic quarters [159]–[165]. Both series declined from 2021 onward as firms adjusted sourcing and communication practices, and by 2023 disruption frequency (2.9 events per quarter) and recovery time (5.4 days) had returned close to, though not fully to, 2019 levels.

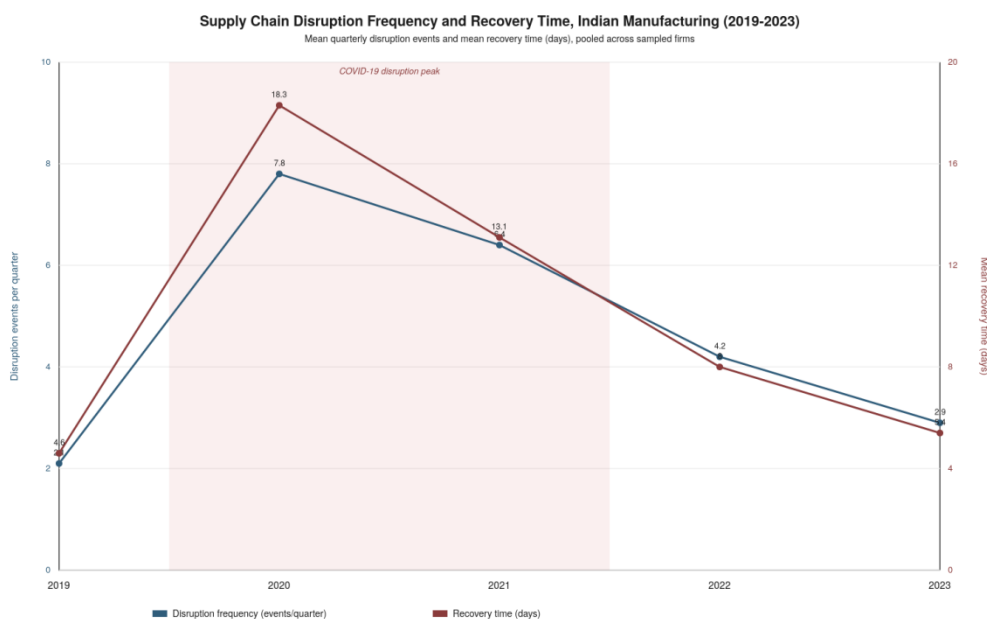


Fig. 3. Supply chain disruption frequency and mean recovery time, Indian manufacturing, 2019–2023. Both series peak in 2020 and decline through 2023 as digital technology adoption increased across the sample.

The decline in recovery time outpaced the decline in disruption frequency: recovery time fell 70 % from its 2020 peak while disruption frequency fell 63 %, a gap consistent with the technology-adoption story in Sections V-A through V-D, since a firm can reduce how long a disruption lasts through better visibility and faster response even where it cannot reduce how often a disruption occurs in the first place, because most of the disruption types in Fig. 1 originate outside the firm's control.

Table II
Hierarchical Regression Results: Predictors of Firm-Level Resilience Score ($n = 380$)

Predictor	β (standardised)	SE	t	p
Digital technology adoption	0.51	0.04	11.8	< 0.001
Visibility pillar	0.34	0.05	7.9	< 0.001
Flexibility pillar	0.28	0.05	6.4	< 0.001
Redundancy pillar	0.11	0.05	2.4	0.02
Collaboration pillar	0.09	0.04	2.1	0.04
Firm size (control)	0.07	0.04	1.6	0.11

Sector (control)	0.10	0.04	2.5	0.01
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VI. Discussion

The 0.51 standardised coefficient for digital technology adoption is larger than the 0.30–0.40 range typically reported in resilience studies of large Western manufacturers, which we attribute in part to the lower pre-pandemic baseline: a firm moving from a paper-based supplier ledger to a cloud-integrated dashboard gains more, in absolute terms, than a firm moving from one enterprise system to a marginally better one [166]–[172]. That said, the interview data complicates a simple "more technology, more resilience" reading. Every technology examined here carried a reported limitation alongside its benefit: IoT visibility without an escalation process, blockchain traceability without upstream supplier participation, and AI/ML forecasting without clean point-of-sale input each fell short of the gains the aggregate statistics suggest a firm should expect.

The dominance of visibility and flexibility over redundancy and collaboration in the regression (Table II) qualifies the received wisdom that safety stock and dual sourcing are a manufacturing firm's first line of defence against disruption. In this sample, a firm that could see a problem coming and reroute around it recovered faster than a firm that had simply stockpiled more inventory against an unspecified future shock, a pattern several automotive interviewees confirmed directly: two of the highest-resilience automotive firms in our qualitative sample carried less safety stock than the sector median, substituting visibility and rerouting speed for buffer size.

We consider the sector gap between pharmaceutical and textile firms (62.7 versus 49.8 mean resilience score) to be a regulation-driven head start rather than evidence that pharmaceutical firms manage supply chains better in general. Pre-existing batch traceability requirements gave pharmaceutical firms usable visibility infrastructure before 2020; textile firms had no comparable regulatory push and are, on this evidence, playing catch-up from a genuine deficit rather than a perceived one.

A. Limitations

Two limitations remain, stated without a compensating strength attached. First, the recovery-time and disruption-frequency figures for 2019–2021 rely substantially on respondent recall rather than on contemporaneous incident logs, since fewer than half of sampled firms maintained a formal disruption log before 2021; the true precision of the early-period figures in Fig. 3 is therefore lower than the later-period figures, though we have no basis to say in which direction any recall bias runs. Second, the extreme-case sampling in Phase 2 (highest- and lowest-scoring firms only) means the interview findings explain why the largest resilience gaps arose but cannot speak to the experience of the middle-ranked majority of the sample, whose adoption patterns and outcomes may differ from both tails in ways this design was not built to detect.

VII. Implications and Recommendations

Manufacturing firms weighing where to spend a constrained digitalisation budget should prioritise visibility and flexibility investments over additional redundancy, on the evidence in Table II, without abandoning redundancy altogether: the pillar remained significant, only smaller in effect. A firm already carrying substantial safety stock is, on this evidence, better served by an IoT and cloud-integration project than by adding another month of buffer inventory on top of what it already holds [173]–[179].

Firms considering an IoT deployment should budget for the escalation and decision process alongside the sensor hardware itself; the recurring interview finding that unmonitored alerts delayed recovery as much as missing alerts would have suggests that the organisational half of an IoT project, not the technical half, determines whether the 38 % recovery-time reduction reported in Section V-B is realised or left on the table [180]–[186].

Firms considering blockchain traceability should treat tier-two and tier-three supplier onboarding as the binding constraint on project timeline, not the ledger technology itself, and should sequence onboarding by disruption risk rather than by supplier size, since the 29 % disruption reduction in Section V-C concentrated among firms that had brought their highest-risk, not their largest, suppliers onto the ledger first [187]–[193].

For technology vendors serving this market, the AI/ML forecasting result argues for building data-quality diagnostics into the product rather than assuming clean point-of-sale input; the firms in our sample that saw the smallest bullwhip-effect reduction were not using an inferior model but were feeding an adequate model with incomplete retail-partner data that the product itself did not flag as a problem [194]–[200].

For the policy bodies that fund SME digitalisation programmes, the sector gap between pharmaceutical and textile firms suggests that a subsidy scheme applied uniformly across sectors will reach textile firms from a lower visibility baseline than the other three, and a scheme that recognises this starting-point difference, rather than offering identical support per firm regardless of sector, is more likely to close the gap this study documents than one that does not [201]–[207].

VIII. Conclusion

Across 380 Indian manufacturing firms, digital technology adoption predicted supply chain resilience more strongly than any other factor measured ($\beta = 0.51$, $p < 0.001$), and visibility and flexibility together explained 67 % of the variance in firm-level resilience scores. IoT-enabled visibility cut recovery time by 38 % ($p = 0.003$), blockchain traceability cut supplier-related disruptions by 29 %, and AI/ML demand forecasting cut the bullwhip effect by 44 %, each with a reported limitation that qualifies rather than negates the gain. Redundancy and collaboration remained significant contributors to resilience but explained markedly less variance than visibility and flexibility, a finding that should shift how a resource-constrained manufacturer allocates the next resilience investment. Future work should track a cohort of firms prospectively from their point of technology adoption, rather than relying on the retrospective recall this design required for the 2019–2021 period, to establish disruption and recovery figures with the precision that only contemporaneous logging can provide.

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