

Artificial Intelligence Adoption and Organisational Performance: Examining Supply Chain Resilience in Manufacturing Firms and Strategic Decision-Making in Indian Start-ups

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Abstract

Most firms no longer ask whether to use artificial intelligence (AI); they ask where it pays off first. This paper looks at two places where the answer seems clearest and the mechanisms quite different: supply chain resilience (SCR) in manufacturing, and strategic decision-making (SDM) in Indian startups. Drawing on the resource-based view, dynamic capabilities theory and organizational information processing theory (OIPT), we argue that AI matters less as a piece of automation and more as an added layer of information-processing capacity. In manufacturing that capacity shows up as earlier warning, steadier inventory and faster rerouting when something breaks. In startups it shows up as cheaper experiments, tighter control of cash and clearer signals about when to change course. The paper is conceptual and draws on published empirical work rather than new primary data. We set out a framework, compare the two settings, and offer a phased adoption roadmap with governance guidance. We also flag the claims that still need testing, because the evidence base, particularly for Indian startups, is thinner than the enthusiasm around it.

Keywords: Artificial Intelligence; Supply Chain Resilience; Strategic Decision-Making; Indian Startups; Dynamic Capabilities; Information Processing

1. Introduction

A decade ago, a firm could get by on good capital discipline and a productive workforce. That is still necessary, but it is no longer enough in markets that swing between shortage and glut, where a port closure or a policy change can undo a year of planning in a week. Under those conditions, how quickly an organisation notices a change, makes sense of it and acts has become a source of advantage in its own right. We call this *cognitive speed*: the time between a signal appearing in the environment and a corrective

decision being carried out.

AI is the most visible way firms are trying to raise that speed. Machine learning can read far more signals than a planning team can, language models can draft and test scenarios in minutes, and optimisation agents can recompute a routing plan while a human dispatcher is still reading the alert. The interesting question for management research is not whether these tools work in a demo but what organisational performance they actually change, and why the answer might differ by setting.

We study two settings that differ sharply. Manufacturers operate long, physical, multi-tier networks in which the main danger is disruption. Indian startups operate in short-cycle, capital-constrained markets in which the main danger is spending scarce resources on the wrong bet. If AI improves performance in both, but through different routes, then a single "AI strategy" template is likely to disappoint one of them. Figure 1 shows the model we develop.

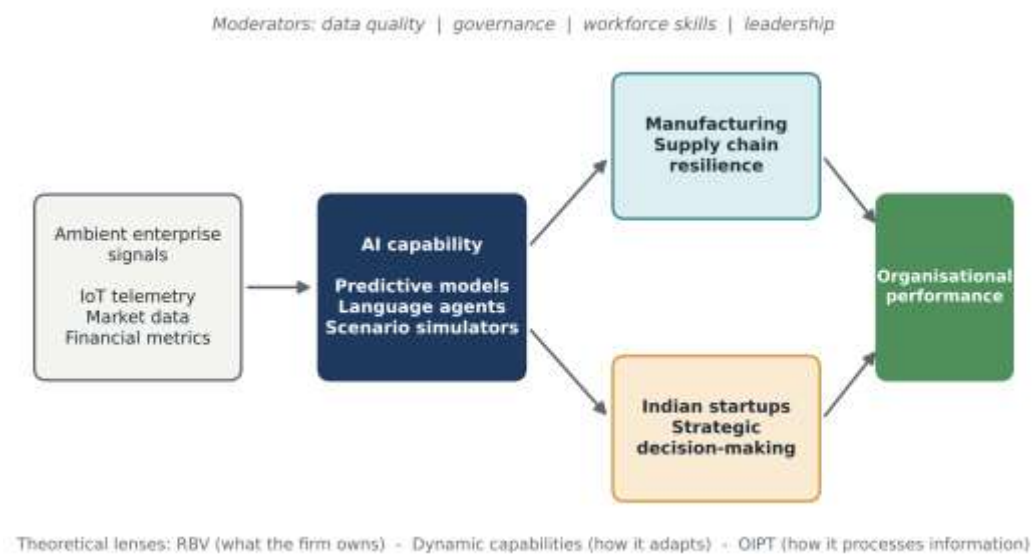


Figure 1. Conceptual model: from enterprise signals to AI capability to performance in two settings.

The paper proceeds as follows. Section 2 sets out the theory. Sections 3 and 4 take manufacturing and startups in turn. Section 5 compares them, Section 6 discusses technical and governance realities, Section 7 gives a managerial roadmap, and Section 8 states limitations and a research agenda before concluding.

2. Theoretical Framework

No single theory explains why AI should change organisational performance, so we combine three that fit together well.

Resource-based view (RBV). Following Barney (1991), a firm earns lasting advantage from resources that are valuable, rare, hard to imitate and hard to substitute. Generic AI tools fail most of these tests because competitors can buy the same models. What may qualify is the combination of a firm's own clean data, models tuned on it, and the processes built around them. Whether that combination is truly inimitable is an empirical matter, and we treat it as a hypothesis rather than a given.

Dynamic capabilities. Teece and colleagues (1997; Teece, 2007) describe the ability to *sense* threats and opportunities, *seize* them through investment, and *transform* the organisation to stay aligned. This sensing-seizing-transforming sequence maps neatly onto what AI systems do in a supply chain, and we use it as

the organising structure in Section 3. Studies of AI-enabled supply chains during COVID-19 reach a similar conclusion, linking AI to resilience through dynamic capabilities (Modgil, Singh, & Hannibal, 2022).

Organizational information processing theory. Galbraith (1974) and Tushman and Nadler (1978) treat firms as information-processing systems. When uncertainty rises, the information the firm needs outgrows what it can handle, and performance suffers unless it either reduces the need or raises its capacity. AI is a clear case of raising capacity. Recent work applies this lens directly to AI and supply chain resilience (Pan et al., 2025; Modgil et al., 2022), which is part of why we use it as the central argument rather than a side note.

Taken together: RBV tells us what the firm owns, dynamic capabilities tell us how it adapts, and OIPT tells us why more processing capacity should help when conditions get harder.

3. Manufacturing: AI and Supply Chain Resilience

Manufacturers have spent the last several years absorbing geopolitical shocks, raw-material price swings and unpredictable demand. Traditional supply chain management leans on historical averages and periodic safety-stock reviews (Christopher, 2016). That works when the future resembles the past and fails when it does not. Systematic reviews of the field find that AI is being applied to demand forecasting, inventory management, logistics optimisation and risk mitigation (Toorajipour et al., 2021; Richey et al., 2023), which are exactly the places where historical-average thinking breaks down.

3.1 Sense, seize, transform

It is useful to ask which part of resilience each AI application supports. Figure 2 sets out the mapping we use.



Figure 2. Dynamic capabilities applied to the supply chain.

- **Sensing: risk visibility.** Models can combine port congestion data, weather feeds, satellite imagery and supplier financial indicators to flag trouble earlier than a periodic review would. How much earlier depends heavily on data quality, and claims of weeks of advance warning should be read as best-case rather than typical.
- **Seizing: inventory and demand balancing.** Modern forecasting models, including deep-learning approaches for time series, can combine local demand signals with upstream production limits. The aim is to damp the bullwhip effect, in which small swings in consumer demand become large swings upstream. Published gains vary by setting, so we avoid quoting a single headline figure.

- **Transforming: adaptive logistics.** Optimisation methods, including reinforcement learning, can re-plan routes and sourcing when cost, transit time or carbon constraints change, with a human approving exceptions rather than every move.

A further strand of work pairs these tools with a digital supply chain twin, a model of the network that can be simulated to test contingency plans before a disruption arrives (Ivanov & Dolgui, 2021; Ivanov, Dolgui, & Sokolov, 2019). Combined with AI, the twin gives managers somewhere safe to rehearse.

3.2 The evidence so far

Empirical support is growing but uneven. A two-stage survey of 107 European companies found that AI use had a direct effect on firm resilience, and that resilience fully mediated the link from AI to firm performance. A recent study applying OIPT reports direct and indirect routes from AI use to supply chain resilience (Pan et al., 2025), and panel evidence from Chinese listed manufacturers suggests AI helps resilience partly through changes in organisational structure and internal controls. We read these together as consistent with our model, while noting that most samples are small, self-reported or drawn from one country.

3.3 What this means

The practical reading is that AI in manufacturing is better understood as insurance than as a cost-cutting tool. Its payoff arrives mostly in bad years, as faster recovery and fewer stockouts. That makes it hard to justify on a standard quarterly return calculation, and boards that judge it only on efficiency gains will tend to under-invest.

4. Indian Startups: AI and Strategic Decision-Making

Indian startups face a particular mix of pressures: investors who now press hard on capital efficiency, customers spread across very different income levels and languages, and a regulatory environment that changes quickly. The national AI strategy published by NITI Aayog (2018) frames AI as a tool for inclusive growth, and startups are among the firms best placed to act on that because they have fewer legacy systems to unwind. For a young firm the main threat is often not disruption but a wrong strategic bet made slowly, or a right one made too late.

4.1 Three routes to better decisions

- **Cheaper market research.** Founders can use language-model agents to draft customer personas, test messaging and pressure-test pricing across segments from metros to smaller towns before spending on field research. Synthetic respondents are no substitute for real customers, and they inherit the biases of the data behind them, but they can narrow the set of ideas worth testing properly. Whether this really shortens experimentation cycles from months to days, as practitioners often claim, is untested in the academic literature.
- **Tighter control of cash.** Predictive models for customer acquisition cost and lifetime value let a founder see how burn and runway change under different scenarios, and adjust earlier.
- **Clearer pivot signals.** Dashboards that combine internal product analytics with outside competitive data can show when unit economics are drifting, giving a team an objective prompt to revisit strategy rather than relying on instinct or hope.

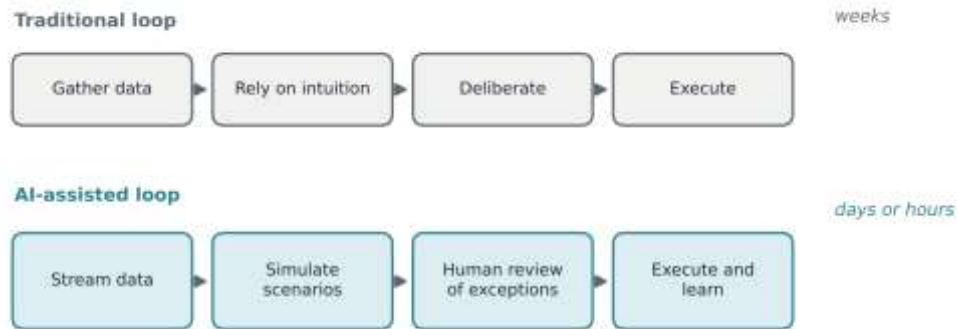


Figure 3. A traditional decision loop compared with an AI-assisted loop (illustrative timings).

Figure 3 contrasts the two loops. The timings are illustrative, not measured. The structural point is that the AI-assisted loop replaces a single deliberation step with continuous simulation, and keeps people for the exceptions that matter.

4.2 What this means

If these routes work, AI changes the economics of strategy for small firms: intelligence that once required a consulting budget becomes a routine, low-cost input. That could narrow the gap between startups and established incumbents. We stress "could". Incumbents hold more data and can also adopt these tools, so the levelling effect is a hypothesis to be tested, not a certainty.

5. Comparing the Two Settings

Both settings use AI to raise information-processing capacity, but the target, the tools and the obstacles differ. Table 1 summarises the contrast.

Table 1. Manufacturing and startup settings compared

Dimension	Manufacturing firms (supply chain resilience)	Indian startups (strategic decision-making)
Primary objective	Cut volatility, keep operations running, contain risk	Spot opportunities early, stretch capital, reach market faster
Typical techniques	Time-series forecasting, reinforcement learning, computer vision	Generative language models, churn and lifetime-value models, Bayesian decision methods
Indicators watched	Time to recover, stockout rate, total cost to serve	LTV/CAC ratio, active-user growth, capital efficiency
Main barriers	Legacy ERP integration, sensor data silos, workforce inertia	Unstructured regional data, model hallucination, founder bias
Shape of the payoff	Steady cost stabilisation and a defensive moat that compounds	Uneven, potentially fast scaling with high early strategic variance

Two patterns stand out. First, the shape of the return differs: manufacturing gains look like a steady, defensive stabilisation, while startup gains look more like a bet with a wider spread of outcomes. Second, the barriers sit in different places. Manufacturers struggle mostly with old systems and the people who run them. Startups struggle mostly with messy, multilingual data and with the temptation to trust fluent but wrong model output.

6. Technical and Governance Realities

It helps to see AI adoption as a feedback system rather than a piece of software bought once. Signals flow in, models turn them into forecasts and options, people review the exceptions, and the results feed back as new data.

6.1 Three technical points

- **Better decisions need better inputs.** A useful way to think about the purpose of these systems is that they should tie the firm's response closely to what is really happening outside, without drowning managers in detail. In information-theoretic terms this is the idea of keeping what is relevant to the decision and discarding the rest. We offer this as a metaphor for design, not as a measurable objective.
- **From rules of thumb to search.** Human heuristics are fast but fail in non-linear conditions. Automated search over many scenarios can surface options that people would not try, although it will also surface options that look good only because the model is wrong.
- **Data is the foundation.** Models are limited by the accuracy, freshness and structure of the data feeding them. In practice, a firm's data architecture constrains its strategy as much as its org chart does.

6.2 Risks to name openly

Four risks recur in the literature and in practice: model errors that look plausible (especially hallucination in language models), bias inherited from training data, over-reliance by managers who stop questioning outputs, and workforce resistance. None is a reason to avoid AI, but each is a reason to design oversight into the process from the start.

7. Managerial Roadmap

We suggest a phased approach, shown in Figure 4. The month ranges are a guide, not a rule; a firm with clean data can move faster, and one with fragmented systems will need longer in the first phase.

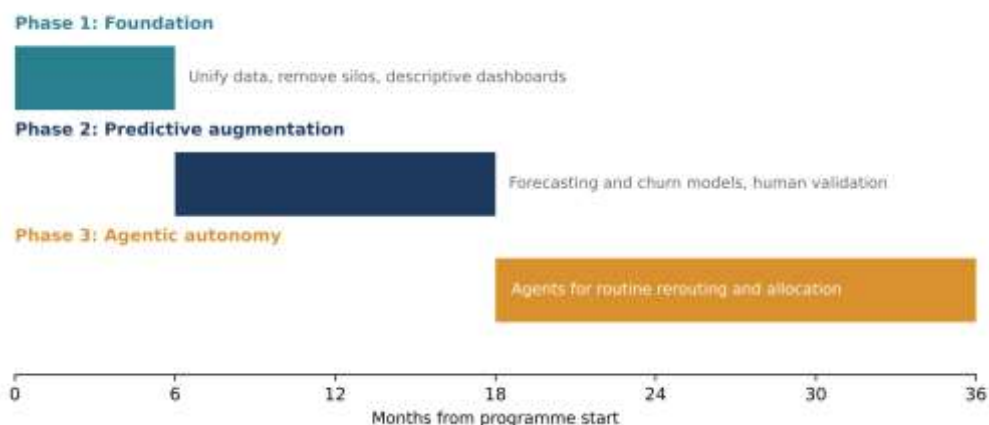


Figure 4. A phased AI adoption roadmap.

- **Phase 1, foundation (about months 0-6).** Unify data definitions, break down silos and put in place basic telemetry and descriptive dashboards. Skipping this phase is the most common reason later projects stall.
- **Phase 2, predictive augmentation (about months 6-18).** Introduce forecasting and churn models for decisions that are frequent and measurable, with a named person validating outputs.
- **Phase 3, agentic autonomy (about month 18 onward).** Allow software agents to handle routine, reversible decisions such as minor rerouting or allocation, and keep scenario modelling available to executives.

Three principles apply across all phases.

- **Avoid the automation trap.** Do not use AI only to speed up an old, clumsy process. Redesign the workflow around what the technology can do (Agrawal, Gans, & Goldfarb, 2022; Iansiti & Lakhani, 2020).
- **Build hybrid governance.** Let systems handle routine, reversible calls and send unusual or high-stakes cases to a person, with clear escalation paths.
- **Invest in literacy.** Shop-floor teams and startup leaders alike need to read probabilistic outputs sensibly, avoiding both blind trust and blanket scepticism (Davenport & Mittal, 2023).

8. Limitations and Research Agenda

This paper is conceptual. It synthesises published work and does not report new primary data, so its propositions are untested here. Several of the claims most often repeated in practitioner discussion, including specific percentage reductions in demand volatility and the shortening of experimentation cycles from months to days, are not firmly established in peer-reviewed research and we have avoided relying on them. Evidence on Indian startups is especially limited.

We see four useful directions for future work: (1) survey or panel studies of Indian startups linking AI use to measurable decision outcomes; (2) comparisons of resilience gains across manufacturing sub-sectors and firm sizes; (3) longitudinal studies of how benefits change as firms move through the phases in Section 7; and (4) experiments on whether human oversight improves or merely slows AI-supported decisions.

9. Conclusion

AI is moving from an optional digital project to a routine part of how firms process information. For manufacturers, its main contribution is resilience: earlier warning, steadier inventory and faster recovery when networks are disrupted. For Indian startups, it is decision quality: cheaper experiments, tighter cash control and clearer signals for changing course. In both cases the benefit comes from combining models with good data, sound workflows and sensible human oversight, not from the models alone.

Firms that treat AI as an information-processing capability, and build it deliberately, are likelier to turn it into durable advantage than those that treat it as a tool to be bolted on. The strength of that conclusion depends on evidence that is still being gathered, and the research agenda above is a first step toward gathering it.

References

1. Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence*. Harvard Business Review Press.

2. Agrawal, A., Gans, J., & Goldfarb, A. (2022). *Power and Prediction: The Disruptive Economics of Artificial Intelligence*. Harvard Business Review Press.
3. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.
4. Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, 37(2), 471-482.
5. Christopher, M. (2016). *Logistics & Supply Chain Management* (5th ed.). Pearson.
6. Davenport, T. H., & Mittal, N. (2023). *All-in on AI: How Smart Companies Win Big with Artificial Intelligence*. Harvard Business Review Press.
7. Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, 4(3), 28-36.
8. Iansiti, M., & Lakhani, K. R. (2020). *Competing in the Age of AI: Strategy and Leadership When Algorithms and Networks Run the World*. Harvard Business Review Press.
9. Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, 32(9), 775-788.
10. Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3), 829-846.
11. Modgil, S., Gupta, S., Stekelorum, R., & Laguir, I. (2022). AI technologies and their impact on supply chain resilience during COVID-19. *International Journal of Physical Distribution & Logistics Management*, 52(2), 130-149.
12. Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: Learning from Covid-19. *The International Journal of Logistics Management*, 33(4), 1246-1268.
13. NITI Aayog. (2018). *National Strategy for Artificial Intelligence: #AIforAll*. Government of India, New Delhi.
14. Pan, H., Zou, N., Wang, R., Ma, J., & Liu, D. (2025). Artificial intelligence usage and supply chain resilience: An organizational information processing theory perspective. *Systems*, 13(9), 724.
15. Richey, R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of Business Logistics*, 44(4), 532-549.
16. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319-1350.
17. Teece, D. J. (2009). *Dynamic Capabilities and Strategic Management: Organizing for Innovation and Growth*. Oxford University Press.
18. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509-533.
19. Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, 122, 502-517.
20. Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. *Academy of Management Review*, 3(3), 613-624.