

Artificial Intelligence and Digital Transformation in Indian Supply Chain Management: A Systematic Review and Meta-Analysis of Applications, Performance Outcomes, and Challenges

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Abstract

Artificial intelligence (AI) and digital transformation are increasingly reshaping supply-chain management through their application to decision-making, operational efficiency, resilience, sustainability, and organisational performance. This study systematically reviews and quantitatively synthesises empirical evidence on AI and digital technologies within the Indian supply-chain ecosystem. Literature was identified from Scopus, Web of Science, ScienceDirect, SpringerLink, and IEEE Xplore, supplemented by manual reference searching. Following PRISMA-based screening, eight eligible studies involving 2,633 participants were retained. The primary random-effects meta-analysis included seven studies with confirmed standardised coefficients ($N = 2,333$). The REML model revealed a significant positive pooled association between AI/digital supply-chain practices and organisational or supply-chain outcomes ($\beta = 0.3166$, 95% CI: 0.2039–0.4293, $Z = 5.507$, $p < .0001$). Considerable heterogeneity was observed ($I^2 = 80.76\%$; $\tau^2 = 0.01819$), while the prediction interval (-0.0603 to 0.6935) indicated substantial contextual variability. Sensitivity analyses supported the stability of the positive pooled association, while publication-bias tests detected no statistically significant small-study asymmetry; however, their power was limited by the small number of studies. Overall, the findings indicate a positive average association between AI-enabled supply-chain transformation and organisational or supply-chain outcomes in the included Indian studies, although the magnitude and direction of these associations may vary across contexts. Organisational readiness, data quality, digital capabilities, sectoral conditions, and responsible AI governance appear to be important factors shaping these relationships.

1. Introduction

Artificial intelligence (AI) is becoming more important in the transformation of supply-chain management, enabling decisions to be made beyond just automated processes to predictive, adaptive and ultimately autonomous digital systems. The global nature of supply chains, rapid technological development, the need for sustainability as well as disruption risks and supply volatility are all placing an increasing need on the market for real time intelligence and data-driven insights and decision support. AI tools are therefore being integrated into various forecasting, procurement, inventory management, supplier assessment, production planning, logistics coordination and risk identification, and customer-facing functions. Culot et al. (2024) have completed a recent systematic review of empirical applications of AI in supply-chain management that highlights that the field is increasingly shifting from isolated experiments to embedding AI technologies in the broader scope of organisations, with substantial implementation and empirical validation gaps. Considering the variance in the technological maturity and organisation readiness of the manufacturing enterprises, logistics providers, export-oriented companies and MSMEs in India, this development holds importance to India.

Generative AI is an essential addition to traditional AI capabilities, allowing supply-chain AI systems to go beyond prediction to generation, scenario building, communication support, and interactive decision making. Generative AI can be used to synthesize unstructured data, create procurement and logistics documents, facilitate supplier communication, aid planning processes, and quickly pull all operational

data together in times of disruption. Therefore, its use in operations and supply chain management has opened up new opportunities for benchmarking the practices of organisations and developed context-specific recommendations (Dubey et al., 2024). But the utility of systems such as these can vary according to the effectiveness of integrating AI-generated information into current workflows, the digital infrastructure and managerial decision processes. The latest studies also show that, with organisational integration and agility (Ma & Chang, 2025), big-data analytics and Artificial Intelligence (AI) can help transform the digital supply chain.

The significant amount of textual and semi-structured data, such as contracts, procurement details, supplier records, transportation details, regulatory documents, customer communications, and disruption reports, generated by supply chains is a reason why Large Language Models (LLMs) are gaining importance. In these information-rich settings, LLMs can assist with information retrieval, knowledge management, communication with suppliers, contract interpretation, and decision-making. They can help analyze vast, diverse information sources, potentially enhancing optimization, risk management, and knowledge utilization within organizations (Srivastava et al., 2024). More recent research has started to categorize LLM applications into planning, sourcing, manufacturing, logistics and coordination aspects, highlighting their potential as seamless components of future intelligent supply-chain architectures (Song et al., 2026). However, the successful adoption of such technology depends on a clear definition of its intended operational use-cases, not just on the adoption of the technology, without alignment with existing supply-chain processes (Sonar et al., 2026).

Explainable Artificial Intelligence (XAI) has become a crucial need for managers to adopt alongside Generative AI and LLMs, as supply chain decisions often have an operational, financial and strategic impact. Explainable systems can help strengthen the decision support process by giving managers the ability to understand algorithmic recommendations and understand the logic behind outputs generated by AI (Olana et al., 2024). In addition, interpretable AI is significant in digitally-integrated and disruptive settings, which have been linked to agile decision-making and enhanced cyber-resilience capabilities (Sadeghi et al., 2024). From an operational perspective, EAI can be used to enhance predictive maintenance and spare parts optimisation by providing better transparency of predictive models and facilitating decision-makers to make maintenance decisions based on model results (Dereci & Tuzkaya, 2024). This recent evidence from perishable-product supply chains also indicates one way in which XAI can help build resilience by providing increased interpretability and consumer-friendliness in supply-chain decision-making (Jauhar et al., 2025).

The transition from Industry 4.0 to Industry 5.0 has a direct connection with the shifting focus of supply chains towards AI. More than just automating and connecting things, more than just a cyber-physical system and more than just data-driven production, Industry 5.0 is a push for increased resilience, sustainability, human-centricity and responsible integration of intelligent technologies. Competitiveness of supply chains is thus increasingly becoming dependent on the ability to integrate advanced technologies with human skills and flexible organizational capacities. Industry 5.0 has been linked to the performance of supply chains, where the focus is on intelligent, resilient and sustainable operational

strategies (Nazarian & Khan, 2024). On a wider scale, AI can enhance supply chain resiliency by improving forecasting capabilities, identifying disruptions, adapting plans, and making more informed decisions in the face of uncertainty (Sunmola & Baryannis, 2024).

With geopolitical uncertainty, disruptions to transportation, environmental shocks, fluctuations in demand, and evolving supplier conditions, resilience is now an important application area for organisations. AI can play a role in resilience by doing predictive analysis, early-warning, scenario modelling and processing complex information in the supply chain quickly. The findings of primary-sector and food-supply-chain scenarios show how AI can be used to shed light on the dynamics of the supply chain and enhance the understanding of what drives food-supply-chain resilience in complex operating environments (Wang et al., 2024). These capabilities are particularly important for the Indian supply chains, which are constrained by infrastructure, lack in geographical concentration, are diverse across sectors and have different levels of digital maturity, potentially compounding the impact of operational disruptions.

Digital twins are another significant technological advance in the creation of AI-powered transformation of the supply chain. Digital twins are digital representations that create dynamic models of physical assets, processes, and networks so that organisations can monitor conditions, simulate different scenarios, test responses to operational disruptions and evaluate them prior to physical implementation. The concept of digital-twin has therefore been suggested as means to improve the resilience and sustainability of supply chains by continuously monitoring the supply chain and making adaptive decisions (Cimino et al., 2024). They are also applicable to lean supply-chain management in which real-time visibility and virtual experimentation can help reduce waste, optimize processes, and enhance the flexibility in allocation of resources, etc. (Guo & Mantravadi, 2024). The implementation of digital-twins, however, strongly relies on integrated data architectures that are able to link physical supply chain processes with analytics and decision supporting environments (Xiros et al., 2025).

In addition, digital twins can enhance sustainability and risk management. The combination of a digital-twin environment and advanced analytical and fuzzy decision methods can enhance supplier selection for enhancing sustainability and systematic consideration of supply-chain risks (Hezam et al., 2024). Likewise, digital-twin (DT) solutions developed for supply-chain recovery can aid the resilience of organizations by allowing them to simulate various disruption scenarios, explore recovery options, and collaboratively plan a response before making changes to physical networks (Ogunsoto et al., 2025). The examples show that digital transformation is no longer just about adopting any one technology, it is about inter-connected technology that integrates AI, analytics, simulation and real-time information.

Despite all these technological innovations, AI usage is not even across industries and organisations. Technological readiness, quality of data, interoperability, skills of the workforce, organisations learning, digital infrastructure, and managerial commitment are all key factors in driving the transition from Industry 4.0 to more advanced intelligent supply-chain ecosystems. AI is entering the realm of increasingly adaptive and integrated supply-chain architectures, as a systematic analysis of AI

integration from Industry 4.0 to Industry 6.0 shows (Samuels, 2025). In developing markets, the disparities between groups can have a significant impact on implementation results, especially in terms of financial resources, workforce's ability to execute, infrastructure and the level of digital maturity.

Research on generative AI is also transforming from the technical side to look more at the requirements for implementation, governance, organisational capacity, and responsible use. Recent synthesis reveals the potential of Generative AI in forecasting, procurement, logistics, knowledge management and decision support, and highlights the challenges related to data quality, security, integration, organisation readiness, and governance (Baruah & Moshref-Javadi, 2026). These challenges underscore the importance of considering AI in a specific context of the organisation and geography rather than expecting that the same benefits of supply chain can be achieved regardless of the technology.

This need is especially strong within India as it has a large manufacturing base, logistics companies, automotive-component companies, maritime and export industries, and a huge MSME industry that has a diverse understanding of digital. Previous empirical research has focused on the adoption of AI, digital traceability, workforce management systems, industrial robots, AI chatbots, resilience frameworks, sustainable supply-chain practices and other digital tools, and the findings of these studies are still sparse and inconsistent at the technology-, industry- and outcome level. Based on these findings, the present study aimed to systematically synthesize quantitative evidence on AI and Industry 4.0 in Supply-chain Management (SCM) in India and using the meta-analytic method to analyse the relationships between operational efficiency, implementation capability, resilience, sustainability, organizational performance and outcomes. The study also synthesises the disparate empirical evidence into a single quantitative approach to evaluate its size, consistency and robustness, and to pinpoint the theoretical, technological and managerial priorities for the next generation of AI-powered Indian supply chains.

2. Methodology

2.1 Review Design and Reporting Framework

A systematic review of literature and quantitative meta-analytic synthesis were used to explore the relationship between artificial intelligence (AI), digital transformation and the outcomes in the supply chain in the context of Indian scenario. The applications were reviewed in manufacturing, supply chain risk management, logistics, maritime transportation and micro, small and medium sized enterprises (MSMEs). The systematic review and study-selection process were reported in accordance with the PRISMA 2020 framework to ensure transparent documentation of study identification, screening, eligibility assessment, and final inclusion.

The unit of analysis was an empirical quantitative study that reported a statistically ascertainable relationship between a predictor related to AI or digital technology and an organisational or supply-chain outcome. Outcomes that were looked at included adoption or implementation, operational efficiency, organisational performance, resilience, sustainability, future technology use and financial performance.

2.2 Information Sources and Search Strategy

The literature search covered Scopus, Web of Science, ScienceDirect, SpringerLink, and IEEE Xplore, supplemented by manual examination of the reference lists of relevant publications. The search covered literature published up to 2026. Search terms included combinations of “artificial intelligence,” “generative AI,” “machine learning,” “AI chatbot,” “industrial robots,” “digitalisation,” and “digital traceability” with supply-chain terms including “supply chain,” “supply chain management,” “logistics,” “manufacturing,” “inventory,” “maritime supply chain,” and “supply chain resilience.” Geographic terms such as “India,” “Indian,” “Indian manufacturing,” and “Indian MSMEs” were also used to restrict the search to the relevant setting. Search expressions were adapted to the indexing structure of the individual databases and applied to titles, abstracts, and keywords.

The search identified 200 records, comprising 170 records from electronic databases and 30 additional records obtained through manual and reference-list searches.

2.3 Eligibility Criteria

Studies were included if they presented primary quantitative data collected from Indian organisations, or if they had a clearly defined sample of Indian organisations and they focused on AI or digital technologies in a supply-chain-related context. The technologies allowed were AI, AI-driven industrial robots, AI-powered chatbots, AI-assisted workforce-management solutions, digital traceability and wider supply-chain digitalisation.

The eligible organisational settings were manufacturing, logistics, maritime operations, supply-chain risk management and MSME operations. Studies had to demonstrate an extractable statistical relationship between a technological predictor and an organizational or/and supply-chain outcome and a coefficient, standard error, test statistic, confidence interval or sufficient information to allow an estimate of uncertainty to be calculated. Only studies in English were included.

These included review articles, conceptual studies and qualitative research, editorials, conference summaries, and technical computational studies, but excluded articles with organisational or supply-chain outcomes. Any study outside India that did not specifically review the Indian companies involved in international supply chains was also not included unless it was relevant to Indian companies.

2.4 Screening and Study Selection

All 170 records were screened by title and abstract after the 30 duplicates were removed from the 200 records that had been identified. A total of 100 records were removed due to the set of rules for AI or digital technologies, supply-chain management, quantitative evidence, and the Indian context. The remaining 70 records were assessed using full-text review.

After full-text review, 62 studies were excluded, of which 20 did not focus on AI and digital supply-chain management, 16 studies did not have empirical evidence from India, 12 studies were review, concept or

qualitative studies, 8 studies did not provide enough methodological or statistical information, and 6 studies did not provide enough quantitative information. A total of eight studies were selected for systematic review and quantitative analysis.

2.5 Data Extraction and Coding

Eight eligible studies were identified and information at the study level was extracted using a structured extraction framework. Variables extracted were author, year of publication, geographic location, number of participants, participant characteristics, research design, analytical method, AI or digital-technology type, predictor variables, outcomes, effect estimates, standard errors, test statistics, probability values, and information needed for risk-of-bias assessment.

Multiple statistical relationships were reported for a number of individual studies, in which case the relationship most directly representing an AI/digital capability or the adoption of AI/digital was selected. Effect codes were used in such a way that positive values always indicated a positive relationship between the technological predictor and the appropriate outcome.

The type and the status of standardisation for the respective coefficient were addressed. Seven studies were found that gave standardised β -type regression path coefficients appropriate for the main quantitative synthesis. The coefficient that Suresh K. has reported. (2024) was derived from an AMOS Estimate/S.E./C.R./P that could not establish a standardisation status. This study was therefore not a part of the overall primary pooled estimate, but was kept in the full eight studies sensitivity analysis.

2.6 Effect Estimates and Confidence Intervals

Principal effect metric (standardised coefficients) was used wherever it was specifically available. The standardised regression coefficient ($\beta = 0.244$) was chosen instead of the unstandardised coefficient in the study by Srinivasan et al. (2025). The standard error was not directly reported but was a standardised coefficient and test statistic were provided, then it was calculated as follows:

$$SE = \frac{|\beta|}{|t|}$$

This procedure was used for studies including Srinivasan et al. (2025) and Pillai et al. (2022), for which standard errors were derivable from the reported coefficient and t -statistic. Derived values were identified separately from directly reported values.

Because the included studies generally did not provide 95% confidence intervals for the selected coefficients, confidence intervals were calculated using the normal approximation:

$$95\% CI = \beta \pm 1.96 (SE)$$

Statistical significance was primarily interpreted using the reported p -values together with calculated confidence intervals. Any discrepancy between the reported significance level and the calculated interval

was retained and disclosed rather than adjusted retrospectively.

2.7 Random-Effects Meta-Analysis and Heterogeneity

The main quantitative synthesis consisted of the seven studies that had standardised coefficient metrics. A random-effects meta-analysis was performed in which variance between studies was estimated by restricted maximum likelihood (REML). The inverse-variance weights were used to ensure that more precise estimates had more weight in the analysis; the random-effects formulation enabled for variation in technology, organisational context, industrial sector and outcome domain.

The pooled coefficient was estimated as:

$$\hat{\theta} = \frac{\sum_{i=1}^k w_i \theta_i}{\sum_{i=1}^k w_i}$$

where θ_i denotes the study-specific standardised coefficient and w_i denotes its random-effects inverse-variance weight.

Cochran's Q statistic, I^2 , Tau^2 (τ^2) and Tau (τ) were used to evaluate statistical heterogeneity. After calculating the I^2 , the proportion of total variation due to between-study heterogeneity was quantified instead of sampling error. A 95% prediction interval was also computed to show the limits for a future similar study to have an effect.

Therefore, the primary model was a generalised coefficient-level synthesis of technologically related predictors and organisational/supply-chain outcomes, rather than a meta-estimate of a common relationship between a construct-to-construct relationship. This distinction was deemed to be necessary because the studies included in this review were conceptually diverse predictors–outcomes combinations.

2.8 Sensitivity and Influence Analyses

Several sensitivity analyses were conducted to evaluate the robustness of the pooled estimate. A full eight-study model was estimated by adding Suresh K. (2024), the coefficient of which wasn't clearly stated as a standardisation. This model was only used as a sensitivity comparison and was not used as the primary estimate.

Secondly, a leave-one-out analysis was performed by successively excluding each study and re-computing the pooled coefficient, confidence interval, I^2 and τ^2 . To check if any single study was unduly influencing the overall association, this analysis was conducted to determine if that was the case.

Additional data-quality sensitivity models were conducted by:

- excluding studies with derived rather than directly reported standard errors;
- excluding the statistically non-significant Panigrahi et al. (2023) relationship;

- restricting the analysis to studies with directly reported standard errors and sufficiently clear coefficient characteristics.

These analyses were intended to determine whether uncertainty in coefficient reporting, or individual study characteristics materially altered the overall pooled association.

2.9 Publication-Bias Assessment

A funnel plot combined with the use of Egger's regression test and the Begg's rank-correlation test was used to explore the possibility of small-study and publication bias. Due to the small number of studies included in the primary analysis ($n = 7$) and the full sensitivity analysis ($n = 8$), the results are interpreted with some caution, as these tests are of low statistical power in small meta-analyses. Thus, a non-significant Egger or Begg test was not seen as an indication that there was no publication bias.

2.10 Risk-of-Bias Assessment and Statistical Software

A structured domain-based approach suitable for cross sectional organizational studies was used to measure the methodological quality. Four domains were assessed: selection bias, confounding, measurement bias and nonresponse bias. Selection bias was judged by sampling methods and the representativeness of the participants in the study; confounding was judged by whether relevant organisational and contextual variables were taken into account; measurement bias was judged by the reliability and validity of the predictor and outcome measures, and nonresponse bias was judged by response rates, exclusions, missing observations, and related reporting.

The assessments at the domain level were given the categories of low, low–moderate, moderate, moderate–high, and high-risk judgments, and an overall judgment was made based on the pattern of the assessments at the domain level. A traffic-light plot was used to report the risk-of-bias results.

Computational statistical procedures were used to organise the data, perform statistical calculations, conduct sensitivity analysis and present the data in graphs. The main meta-analysis employed a random-effects REML specification, and the rest of the quantitative synthesis included heterogeneity, prediction intervals, influence analyses, and publication-bias diagnostics.

3. Results

3.1 Study Identification and Selection

The search process identified 200 potentially relevant records, including 170 records retrieved through Scopus, Web of Science, ScienceDirect, SpringerLink, and IEEE Xplore and 30 records identified through manual and reference-list searches. After removal of 30 duplicates, 170 unique records were screened by title and abstract. Of these, 100 records were excluded at the initial screening stage, leaving 70 full-text reports for eligibility assessment. Sixty-two full-text reports were subsequently excluded, resulting in

eight studies being retained for the systematic review and quantitative synthesis. The study-selection process and final inclusion counts are summarised in Table 1.

Table 1
Study identification, screening, eligibility, and final inclusion process

Selection stage	Number of records
Records identified through database searches	170
Records identified through manual/reference-list searches	30
Total records identified	200
Duplicate records removed	30
Records screened by title and abstract	170
Records excluded during initial screening	100
Full-text reports assessed for eligibility	70
Full-text reports excluded	62
Studies included in systematic review	8
Studies retained for quantitative synthesis	8

The 62 full-text exclusions consisted of studies not directly addressing AI-enabled or digital supply-chain management ($n = 20$), studies without Indian empirical evidence ($n = 16$), review/conceptual/qualitative articles ($n = 12$), studies with inadequate methodological or statistical information ($n = 8$), and studies with incomplete quantitative data ($n = 6$). The complete study identification, screening, eligibility, and inclusion process is illustrated in Fig. 1.

3.2 Characteristics of the Included Studies

The eight eligible studies represented 2,633 participants and covered different components of the Indian supply-chain ecosystem, including manufacturing SMEs, logistics companies, automotive-component firms, maritime exporters, risk-management professionals, and enterprises adopting sustainable supply-chain practices. The studies predominantly employed cross-sectional quantitative designs, with PLS-SEM or SEM representing the most frequently used analytical approaches. Regression analysis, ANOVA, and independent-samples testing were also reported in selected studies.

The applications investigated were heterogeneous and included green supply-chain management, digital traceability, AI-supported resilience frameworks, AI-enabled workforce management, AI adoption in risk management, AI-empowered industrial robots, AI adoption for maritime resilience, and AI-chatbot adoption for sustainable supply-chain performance. The methodological, sample, and technological characteristics of the included studies are presented in Table 2.

Table 2
Methodological, sample, and technological characteristics of the eight included studies

Study	Design/analysis	Context	N	Population	Principal AI/digital focus
Gupta et al. (2025)	Cross-sectional; PLS-SEM	India	389	Managers from manufacturing enterprises	Green supply-chain practices and sustainability
Srinivasan et al. (2025)	Cross-sectional; regression	India	385	Manufacturing SME managers	Digital traceability and efficiency
Suresh K. (2024)	Mixed-method cross-sectional; ANOVA, <i>t</i> -tests, SEM	India	300	Logistics executives	AI implementation and resilience
Kumar et al. (2022)	Cross-sectional; SEM	India	307	MSME employees	AI-powered workforce management
Paul et al. (2022)	Cross-sectional; PLS-SEM	India	278	Executives, risk professionals, AI consultants	AI adoption in supply-chain risk management
Pillai et al. (2022)	Cross-sectional; PLS-SEM	India	460	Automotive-component managers/owners	AI-empowered industrial robots
Shrivastav and Joshi (2026)	Cross-sectional; PLS-SEM	India–Thailand corridor	268	Indian MSME exporters and maritime professionals	AI adoption and maritime resilience
Panigrahi et al. (2023)	Cross-sectional; PLS-SEM	India	246	Manufacturing SME managers	AI-chatbot adoption and sustainable performance

3.2.1 Publication Trend Analysis

The publication-year distribution of the eight included studies indicates that empirical research on AI and digital transformation in Indian supply chains has developed mainly in the most recent period. Three of the included studies were published in 2022, representing 37.5% of the evidence base, while one study was published in 2023 (12.5%), one in 2024 (12.5%), two in 2025 (25.0%), and one in 2026 (12.5%).

This pattern shows that five of the eight included studies (62.5%) were published between 2023 and 2026, indicating increasing recent attention to AI-enabled and digitally transformed supply-chain practices. The earlier 2022 studies primarily examined AI adoption, workforce-management systems, and AI-enabled industrial robotics, whereas subsequent studies expanded toward AI chatbots, resilience frameworks, digital traceability, sustainable supply-chain practices, and maritime resilience. The

progression therefore suggests a gradual broadening of the research agenda from organisational adoption and automation toward more diverse applications involving resilience, sustainability, information visibility, and digitally enabled decision-making. The year-wise distribution of the included empirical studies is presented in Table 3.

Table 3
Year-wise publication trend of the eight studies included in the systematic review and quantitative synthesis

Publication year	Included studies	Number of studies	Percentage (%)
2022	Kumar et al.; Paul et al.; Pillai et al.	3	37.5
2023	Panigrahi et al.	1	12.5
2024	Suresh K.	1	12.5
2025	Gupta et al.; Srinivasan et al.	2	25.0
2026	Shrivastav & Joshi	1	12.5
Total		8	100.0

3.3 Distribution of Technologies, Industries, and Outcomes

The included evidence covered several distinct technological and organisational applications. AI adoption and implementation were represented by Paul et al. (2022) and Shrivastav and Joshi (2026), while AI-enabled industrial robotics was investigated by Pillai et al. (2022). Panigrahi et al. (2023) examined AI-chatbot adoption, Kumar et al. (2022) evaluated AI-powered workforce management, Srinivasan et al. (2025) focused on digital traceability, and Suresh K. (2024) assessed data quality and integration within an AI-supported resilience framework. Gupta et al. (2025) examined digitally enabled green supply-chain practices.

At the outcome level, the studies broadly addressed implementation capability, operational efficiency, resilience, sustainability, management performance, revenue growth, and future technology use. This distribution demonstrates the multidimensional nature of AI and digital transformation across Indian supply chains, while also indicating considerable conceptual heterogeneity across the effect relationships. The technological diversity identified across the included studies is synthesized in Fig. 5, which classifies major AI and digital technology categories according to their functional supply-chain applications and associated organizational outcomes.

The distribution of the included studies by technology, industry context, and principal outcome domain is summarised in Table 3.

Table 3

Distribution of included studies by technology, industry context, and principal outcome domain

Study	Technology/application category	Industry/context	Main outcome domain
Gupta et al. (2025)	Green/digital supply-chain practices	Manufacturing	Management/sustainability performance
Srinivasan et al. (2025)	Digital traceability	Manufacturing SMEs	Supply-chain efficiency
Suresh K. (2024)	AI-supported data integration	Logistics	Resilience/framework effectiveness
Kumar et al. (2022)	AI workforce management	MSMEs	Revenue growth
Paul et al. (2022)	AI adoption	Supply-chain risk management	AI implementation
Pillai et al. (2022)	AI-empowered industrial robots	Automotive components	Potential future use
Shrivastav and Joshi (2026)	AI adoption	Maritime/MSME export	Supply-chain resilience
Panigrahi et al. (2023)	AI chatbots	Manufacturing SMEs	Sustainable supply-chain performance

3.4 Individual Quantitative Effects

All eight extracted point estimates were positive, although their magnitude and statistical significance varied considerably. Paul et al. (2022) reported the largest verified standardised coefficient for AI adoption and implementation ($\beta = 0.5565$), followed by Shrivastav and Joshi (2026) for AI adoption and maritime resilience ($\beta = 0.462$). Pillai et al. (2022) reported an effect of $\beta = 0.348$, while Gupta et al. (2025) reported $\beta = 0.274$.

For Srinivasan et al. (2025), the standardised regression coefficient of $\beta = 0.244$ was retained rather than the previously used unstandardised coefficient of 0.258. Panigrahi et al. (2023) showed a positive but statistically non-significant relationship ($p = .066$). Suresh K. (2024) reported an effect of 0.378, although its standardisation status could not be confirmed and the study was therefore excluded from the primary pooled analysis. The verified study-level effect estimates used in the quantitative synthesis are reported in Table 4.

Table 4
Verified individual effect estimates used in the quantitative synthesis

Study	Predictor → outcome	Effect	SE	95% CI	Statistical significance	Direction
Gupta et al. (2025)	Green product/design → management performance	0.274	0.044	0.188–0.360	$p < .001$	Positive
Srinivasan et al. (2025)	Digital traceability → supply-chain efficiency	0.244	0.044 [⊠]	0.158–0.330 [⊠]	$p < .001$	Positive
Suresh K. (2024)	Data quality/integration → framework effectiveness	0.378 [⊠]	0.116	0.151–0.605	$p < .001$	Positive
Kumar et al. (2022)	AI workforce management → revenue growth	0.131	0.074	–0.014–0.276 [⊠]	Reported $p = .048$	Positive
Paul et al. (2022)	AI adoption → AI implementation	0.5565	0.0708	0.418–0.695	$p < .001$	Positive
Pillai et al. (2022)	AI-robot adoption → potential use	0.348	0.1047 [⊠]	0.143–0.553 [⊠]	$p < .01$	Positive
Shrivastav and Joshi (2026)	AI adoption → maritime resilience	0.462	0.052	0.360–0.564	$p < .001$	Positive
Panigrahi et al. (2023)	AI-chatbot adoption → sustainable performance	0.182	0.099	–0.012–0.376	$p = .066$ [⊠]	Positive

Notes

⊠ SE and CI derived from the standardised coefficient and reported t -statistic; ⊠ standardisation status was not explicitly confirmed, and the estimate was therefore excluded from the primary model; ⊠ the calculated CI crosses zero despite the reported $p = .048$ and was retained transparently; ⊠ SE and CI were derived from β/t ; ⊠ the source study reported this relationship as non-significant at $\alpha = .05$. All 95% CIs were calculated using the normal approximation where not directly available.

3.5 Primary Random-Effects Meta-Analysis

The primary meta-analysis included seven studies ($N = 2,333$) with confirmed standardised coefficient metrics. Suresh K. (2024) was excluded from the primary model because the standardisation status of the AMOS estimate could not be established.

Using a REML random-effects model, the pooled effect was 0.3166 (95% CI: 0.2039–0.4293), with an SE of 0.0575. The pooled association was statistically significant ($Z = 5.507, p < .0001$), indicating a positive average association between AI/digital supply-chain practices and organisational or supply-chain outcomes across the included studies. However, this pooled estimate should be interpreted as an average across heterogeneous study contexts rather than as evidence of a uniform effect.

Considerable between-study heterogeneity was observed, with Cochran’s $Q (6) = 31.185, p < .0001, I^2 = 80.76\%, \tau^2 = 0.01819$, and $\tau = 0.1349$. The 95% prediction interval ranged from -0.0603 to 0.6935 and crossed zero. Therefore, although the pooled average association was positive and statistically significant, substantial heterogeneity and the prediction interval indicate that the magnitude, and potentially the direction, of the association may vary across comparable organisational, technological, and sectoral settings. A future study conducted in a similar context could therefore plausibly report a weaker, null, or potentially negative association. The principal results of the seven-study REML random-effects meta-analysis are presented in Table 5.

Table 5
Summary statistics for the primary seven-study REML random-effects meta-analysis

Parameter	Result
Number of studies (<i>k</i>)	7
Total sample size	2,333
Pooled effect	0.3166
Pooled SE	0.0575
95% CI	0.2039–0.4293
<i>Z</i>	5.507
Overall <i>p</i>	< .0001
Cochran’s <i>Q</i>	31.185
df	6
<i>Q p</i> -value	< .0001
τ^2	0.01819
τ	0.1349
I^2	80.76%
H^2	5.20
95% prediction interval	–0.0603–0.6935

3.6 Study Weights and Forest-Plot Distribution

Under the REML random-effects model, individual study weights ranged from 11.34% to 16.42%. Gupta et al. (2025) and Srinivasan et al. (2025) each contributed 16.42%, whereas Pillai et al. (2022) had the lowest weight at 11.34%. The relatively balanced distribution of weights indicates that the pooled result was not dominated exclusively by a single highly precise study. The random-effects weights assigned to the studies included in the primary meta-analysis are shown in Table 6.

Table 6
Random-effects weights of studies included in the primary meta-analysis

Study	Random-effects weight (%)
Gupta et al. (2025)	16.42
Srinivasan et al. (2025)	16.42
Kumar et al. (2022)	13.96
Paul et al. (2022)	14.24
Pillai et al. (2022)	11.34
Shrivastav and Joshi (2026)	15.82
Panigrahi et al. (2023)	11.81

The study-specific effects, 95% confidence intervals, random-effects weights, and pooled REML estimate are visualised in Fig. 2.

3.7 Full Eight-Study Sensitivity Model

To evaluate whether exclusion of Suresh K. (2024) materially influenced the findings, a secondary model including all eight studies was estimated. The full model produced a pooled coefficient of 0.3225 (95% CI: 0.2207–0.4242; $Z = 6.209$, $p < .0001$). Heterogeneity remained substantial, with $Q(7) = 31.467$, $p = .0001$; $I^2 = 77.75\%$; $\tau^2 = 0.01589$. The corresponding prediction interval was – 0.0112 to 0.6561.

The close similarity between the seven-study primary estimate (0.3166) and the eight-study sensitivity estimate (0.3225) indicates that inclusion of the study with unclear standardisation status did not materially alter the pooled direction or magnitude. Nevertheless, the persistence of substantial heterogeneity in the eight-study model indicates that the stability of the average pooled estimate should not be interpreted as evidence of uniform associations across technologies, sectors, organisational contexts, or outcome domains. A comparison of the primary seven-study model and the full eight-study sensitivity model is provided in Table 7.

Table 7
Comparison of the primary and full random-effects models

Model	k	N	Pooled effect	95% CI	I ²	τ ²	95% prediction interval
Primary model	7	2,333	0.3166	0.2039–0.4293	80.76%	0.01819	–0.0603–0.6935
Full sensitivity model	8	2,633	0.3225	0.2207–0.4242	77.75%	0.01589	–0.0112–0.6561

3.8 Leave-One-Out Sensitivity Analysis

Leave-one-out analysis showed that the pooled estimate remained statistically significant regardless of which individual study was excluded. Pooled estimates ranged from 0.2786 to 0.3469, with all corresponding 95% confidence intervals remaining above zero. Paul et al. (2022) exerted the greatest individual influence; its removal reduced the pooled estimate to 0.2786 and lowered I² to 72.64%. The statistical significance and positive direction of the pooled average association were retained across all leave-one-out models, although substantial heterogeneity persisted. The results of the leave-one-out sensitivity analysis are summarised in Table 8.

The stability of the pooled coefficient across all seven iterations indicates that the main finding was not dependent on any single study. However, this stability should be interpreted as evidence of robustness of the pooled average association rather than evidence of homogeneous effects across the included studies.

Table 8
Leave-one-out sensitivity analysis of the seven-study primary model

Study removed	Pooled effect	95% CI	I ² (%)	τ ²	Interpretation
Gupta et al. (2025)	0.3243	0.1894–0.4592	83.33	0.02281	Conclusion unchanged
Srinivasan et al. (2025)	0.3302	0.1980–0.4624	81.91	0.02170	Minimal influence
Kumar et al. (2022)	0.3469	0.2343–0.4594	79.47	0.01502	Pooled effect increased modestly
Paul et al. (2022)	0.2786	0.1810–0.3762	72.64	0.01020	Largest individual influence
Pillai et al. (2022)	0.3121	0.1829–0.4413	83.91	0.02187	Minimal influence
Shrivastav and Joshi (2026)	0.2893	0.1694–0.4091	76.63	0.01709	Moderate influence
Panigrahi et al. (2023)	0.3347	0.2118–0.4575	82.92	0.01926	Conclusion unchanged

The stability of the pooled coefficient across all seven iterations indicates that the main finding was not dependent on any single study.

3.9 Data-Quality Sensitivity Analyses

Additional sensitivity analyses examined the influence of derived standard errors, statistical non-significance, and stricter inclusion criteria. Excluding Srinivasan et al. (2025) and Pillai et al. (2022), whose SEs were derived rather than directly reported, produced a pooled estimate of 0.3263 (95% CI: 0.1691–0.4836). Exclusion of the non-significant Panigrahi et al. (2023) effect produced an estimate of 0.3347 (95% CI: 0.2118–0.4575).

A stricter four-study model restricted to Gupta et al. (2025), Kumar et al. (2022), Paul et al. (2022), and Shrivastav and Joshi (2026) yielded a pooled estimate of 0.3565 (95% CI: 0.1753–0.5377). Across these specifications, pooled estimates remained within approximately 0.317–0.357, and all 95% CIs excluded zero. However, I^2 remained high across all models, ranging from approximately 78% to 88%, indicating persistent between-study heterogeneity. Accordingly, these sensitivity analyses support the stability of the direction of the pooled association, but they do not eliminate the substantial between-study heterogeneity. The results of the additional data-quality sensitivity analyses are presented in Table 9.

Table 9
Data-quality sensitivity analyses of the pooled association

Sensitivity model	k	N	Pooled effect	95% CI	I^2 (%)	τ^2
Primary model	7	2,333	0.3166	0.2039–0.4293	80.76	0.01819
Full eight-study model	8	2,633	0.3225	0.2207–0.4242	77.75	0.01589
Excluding derived-SE studies	5	1,488	0.3263	0.1691–0.4836	85.52	0.02743
Excluding Panigrahi et al. (2023)	6	2,087	0.3347	0.2118–0.4575	82.92	0.01926
Strict four-study model	4	1,242	0.3565	0.1753–0.5377	87.94	0.03048

3.10 Publication-Bias Assessment

Visual assessment of funnel-plot symmetry was supplemented by Egger’s regression and Begg’s rank-correlation tests. In the seven-study primary model, Egger’s test produced an intercept of 0.2232 ($t = 0.0728$, $p = .9448$), while Begg’s test yielded Kendall’s $\tau = 0.000$, $p = 1.000$. Neither test identified statistically detectable small-study asymmetry. Given the small number of studies included in the primary analysis, however, these tests have limited statistical power and cannot exclude the possibility of publication bias. Publication-bias diagnostics for the primary and full meta-analytic models are reported in Table 10.

Table 10
Publication-bias diagnostics for the primary and full meta-analytic models

Test	Primary model (k = 7)	Full model (k = 8)
Egger intercept	0.2232	0.4534
Egger SE	3.0682	2.3876
Egger <i>t</i>	0.0728	0.1899
Egger <i>p</i>	.9448	.8557
Begg Kendall's τ	0.0000	0.1091
Begg <i>p</i>	1.0000	.7084

The non-significant tests therefore indicate no statistically detectable asymmetry but should not be interpreted as evidence that publication bias is absent. Given that both models contained fewer than ten studies, the possibility of publication bias or small-study effects remains uncertain. The distribution of effect estimates according to their standard errors and the assessment of small-study asymmetry are illustrated in Fig. 3.

3.11 Risk-of-Bias Assessment

Risk of bias varied across the eight studies. Pillai et al. (2022) showed the strongest methodological profile and received an overall low-risk classification. Gupta et al. (2025), Srinivasan et al. (2025), Kumar et al. (2022), Paul et al. (2022), Shrivastav and Joshi (2026), and Panigrahi et al. (2023) were classified overall as moderate risk. Suresh K. (2024) received the highest overall risk classification because concerns were elevated across selection, confounding, measurement, and nonresponse domains. The domain-level and overall risk-of-bias assessments of the included studies are summarised in Table 11.

Table 11
Domain-level and overall risk-of-bias assessment of the eight included studies

Study	Selection bias	Confounding	Measurement bias	Nonresponse bias	Overall risk
Gupta et al. (2025)	Moderate	Moderate	Low	Low	Moderate
Srinivasan et al. (2025)	Moderate	Moderate	Moderate	Moderate	Moderate
Suresh K. (2024)	Moderate–High	High	Moderate–High	Moderate–High	High
Kumar et al. (2022)	Moderate	Moderate	Low	Moderate	Moderate
Paul et al. (2022)	Moderate	Moderate	Low	Moderate–High	Moderate
Pillai et al. (2022)	Low	Moderate	Low	Low	Low
Shrivastav and Joshi (2026)	Moderate	Moderate	Moderate	Low	Moderate
Panigrahi et al. (2023)	Moderate	Moderate	Moderate	Low	Moderate

The domain-specific and overall risk-of-bias ratings across the eight included studies are presented in Fig. 4.

3.12 Overall Synthesis of Findings

Taken together, the evidence indicates a positive pooled average association between AI/digital supply-chain practices and organisational or supply-chain outcomes in the included Indian studies. The seven-study primary model yielded a pooled standardised coefficient of 0.317, while the eight-study sensitivity model produced a closely comparable estimate of 0.323. The direction and approximate magnitude of the pooled association remained stable across leave-one-out and data-quality sensitivity analyses.

However, the consistently high heterogeneity and prediction intervals crossing zero indicate substantial contextual variation across technologies, industries, organisational settings, and outcome domains. The pooled coefficient should therefore be interpreted as a summary of heterogeneous study-level relationships rather than as a single generalisable effect applicable uniformly across Indian supply chains. Accordingly, these findings do not imply that AI/digital supply-chain practices will produce effects of the same magnitude, or necessarily in the same direction, across all comparable settings.

Drawing on the overall synthesis, Fig. 6 integrates AI and digital technology capabilities, organisational and technological enablers, AI-enabled supply-chain capabilities, and their resulting performance

outcomes within a unified conceptual framework.

4. Discussion

This systematic review and meta-analysis identified a statistically significant positive pooled association between AI/digital supply-chain practices and organisational or supply-chain outcomes in the included Indian studies. The pooled standardised effect in the primary model was 0.3166 (95% CI: 0.2039–0.4293; $Z = 5.507$, $p < .0001$), while the eight-study sensitivity model produced a closely comparable estimate of 0.3225. However, the substantial heterogeneity ($I^2 = 80.76\%$) and the prediction interval crossing zero indicate considerable variation across technologies, sectors, organisational settings, and outcome domains. Accordingly, the pooled estimate should be interpreted as an average association across heterogeneous studies rather than as evidence of a uniform effect of AI across Indian supply chains. This pattern is consistent with a capability-led view, in which technological resources may generate value when effectively integrated into operational and managerial processes (Jackson et al., 2024).

The findings can also be interpreted through complementary theoretical perspectives. Based on the Technology–Organisation–Environment (TOE) framework, AI adoption depends on technological preparedness, organisational conditions, and the external operating environment. The Resource-Based View (RBV) similarly suggests that AI systems, digital infrastructure, data resources, and employee capabilities may become strategic resources when they are effectively integrated into organisational routines. Dynamic Capability Theory further emphasises the need to sense technological opportunities, seize relevant innovations, and reconfigure supply-chain resources in response to changing markets and disruptions. These interpretations complement the Supply Chain 5.0 perspective, in which intelligent technologies are linked with resilience, sustainability, human-centricity, and responsible governance. Thus, the observed associations are more appropriately interpreted as reflecting interactions among technological capability, organisational resources, adaptability, and implementation context rather than the effects of technology adoption alone.

Among the included studies, AI adoption showed the largest verified positive coefficient in relation to subsequent implementation, suggesting that greater adoption was associated with stronger implementation capability in the examined organisational setting (Paul et al., 2022). Digital traceability was positively associated with supply-chain efficiency, highlighting the importance of visibility, transparency, and real-time information sharing in manufacturing SMEs (Srinivasan et al., 2025). AI-powered workforce management was also positively associated with MSME revenue growth, although the magnitude of the relationship was comparatively modest, suggesting that employee skills, digital capabilities, managerial acceptance, and infrastructure may remain important complementary factors (Kumar et al., 2022). Beyond the studies included in the quantitative synthesis, broader literature suggests that Generative AI may support digital supply-chain performance where organisations possess sufficient coordination and adaptive capacity to integrate AI-generated information into operational

decision-making (Li et al., 2024). Similarly, Generative AI has been associated with organisational adaptability and innovation ambidexterity in manufacturing contexts (Al-Khatib et al., 2024).

Although Generative AI was not uniformly represented in the pooled analysis, broader literature indicates that it may extend traditional predictive and automation functions by supporting knowledge generation, scenario development, supplier communication, procurement, inventory planning, and interactive decision support. These capabilities may also support disruption management through the generation of alternative response scenarios and the synthesis of complex operational information. However, their practical value is likely to depend on adequate data infrastructure, human validation, cybersecurity safeguards, and governance mechanisms. This consideration is particularly relevant in Indian MSMEs, where digital maturity and technological capabilities can vary substantially across organisations.

Resilience also emerged as an important outcome domain. AI adoption was positively associated with maritime supply-chain resilience among Indian MSME exporters, suggesting that predictive analytics, real-time monitoring, and responsive decision-making may be relevant in disruption-sensitive maritime environments (Shrivastav & Joshi, 2026). Beyond the pooled evidence, recent literature suggests that Generative AI may support resilience through scenario generation, disruption forecasting, and adaptive planning, although these potential benefits remain dependent on implementation quality and governance (Boone et al., 2025). Data quality and integration were also identified as important factors in AI-supported resilience frameworks, reinforcing the view that intelligent systems depend on reliable and integrated organisational information (Suresh K., 2024). Similarly, broader research suggests that explainable AI may support resilience in perishable-product supply chains by improving transparency and context-sensitive decision support (Jauhar et al., 2025).

Other dimensions of digital transformation include automation and sustainability. In automotive-component manufacturing, the perceived value and implementation experience of AI-empowered industrial robots were positively associated with potential future technology use (Pillai et al., 2022). This relationship is compatible with the industry 5.0 emphasis on human-centric, resilient, and sustainable technology adoption. Management performance was also positively associated with green supply-chain practices, indicating that digital and sustainability-oriented practices may be linked with organisational performance (Gupta et al., 2025). Although digital twins were not directly represented across the pooled studies, broader literature suggests that they may support real-time process simulation, visibility, resource optimisation, and disruption assessment (Zaidi et al., 2024).

The sustainability-related findings were more context-dependent. AI-chatbot adoption showed a positive but statistically non-significant relationship with sustainable supply-chain performance, indicating that the available evidence does not establish a direct measurable association in that setting (Panigrahi et al., 2023). Beyond the quantitative synthesis, research on explainable AI suggests that greater interpretability may support implementation by helping decision-makers understand and justify algorithmic recommendations (Olan et al., 2025). Explainability has also been associated with agile decision-making and cyber-resilience (Sadeghi R. et al., 2024). Transparency, accountability, and trust

therefore remain important considerations in AI-enabled decision processes, while human–AI collaboration may be more valuable when these principles are embedded in organisational governance (Vann Yaroson et al., 2025). Ethical issues related to bias, privacy, cybersecurity, accountability, and human oversight should consequently be considered in the responsible implementation of AI-enabled supply-chain systems (Brintrup et al., 2025). Recent studies likewise emphasise the strategic opportunities and ethical risks associated with AI in supply-chain management and the need for robust governance frameworks (Wellbrock et al., 2025).

The substantial heterogeneity observed in the pooled model is likely to reflect methodological and contextual diversity across the included studies, including differences in AI technology type, industrial sector, organisational size, predictor definition, outcome measurement, analytical method, sample composition, and level of digital maturity. Consequently, the pooled estimate should be interpreted as a broad cross-study summary rather than as a technology-specific effect size or a single common causal effect.

Overall, the evidence supports a positive average association between AI/digital supply-chain practices and efficiency, resilience, sustainability, decision-making, and organisational outcomes in the included studies, but these associations varied substantially across contexts. Their magnitude appears to depend on factors such as data quality, workforce capability, organisational readiness, coordination, adaptive capacity, infrastructure, and responsible governance. The persistence of heterogeneity therefore supports the need for future technology-specific, sector-specific, and longitudinal studies rather than assuming a uniform effect of AI adoption across the Indian supply-chain ecosystem.

5. Limitations

This review has several limitations that should be considered when interpreting the findings. First, the overall evidence base was relatively small, comprising eight eligible studies, with seven studies included in the primary meta-analysis. Most of the included investigations employed cross-sectional designs, which limits causal inference and means that the observed relationships should be interpreted primarily as associations rather than direct effects. Second, substantial statistical and contextual heterogeneity was present across the included studies, reflecting differences in AI and digital technologies, industrial sectors, organisational settings, predictor definitions, outcome measures, analytical approaches, sample characteristics, and levels of digital maturity. The 95% prediction interval also crossed zero, indicating that future comparable studies may report weaker, null, or potentially negative associations. Third, the quantitative synthesis combined conceptually diverse predictor–outcome relationships; therefore, the pooled coefficient represents a broad cross-study average rather than a single common technology-specific effect. In addition, standard errors for some studies were derived from reported coefficients and test statistics, while the standardisation status of one study estimate could not be confirmed. Publication-bias assessments were also constrained by the small number of studies, reducing the power of Egger’s and Begg’s tests. Finally, the review was restricted to English-language studies and focused

primarily on selected Indian organisational and industrial contexts, which may limit the generalisability of the findings to other sectors or geographic settings.

6. Conclusion

This systematic review and meta-analysis provide quantitative evidence of a positive average association between AI/digital supply-chain practices and organisational or supply-chain outcomes in the included Indian studies. The evidence spans manufacturing, MSMEs, logistics, automotive components, risk management, and sustainability-oriented applications. The primary REML meta-analysis yielded a significant pooled standardised effect of 0.3166. However, the substantial heterogeneity ($I^2 = 80.76\%$) and the prediction interval crossing zero indicate that the magnitude, and potentially the direction, of these associations may vary across technologies, industries, organisational contexts, and outcome domains. The findings therefore suggest that successful AI-enabled digital transformation depends not only on technological adoption but also on data quality, organisational readiness, workforce capabilities, digital infrastructure, interorganisational coordination, explainability, and responsible governance. Emerging technologies such as Generative AI, large language models, digital twins, and explainable AI may offer additional opportunities for forecasting, decision support, resilience, and supply-chain visibility, although these applications require stronger empirical validation in the Indian context. Future research should prioritise longitudinal and multi-sector designs, larger samples, standardised outcome measures, and direct comparisons of specific AI technologies. Overall, the findings support a positive but context-dependent relationship between AI-enabled digital transformation and supply-chain outcomes rather than a uniform effect across the Indian supply-chain ecosystem.

Declarations

Author Contributions: Supreeth S contributed to the conceptualisation, methodology, formal analysis, and writing of the original draft. Supreeth S performed the investigation, validation, and data curation. Dr. Sandhya S was responsible for supervision, project administration, and writing of the manuscript. All authors reviewed and approved the final version of the manuscript.

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Conflicts of interest: The authors declare no competing interests.

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Figures

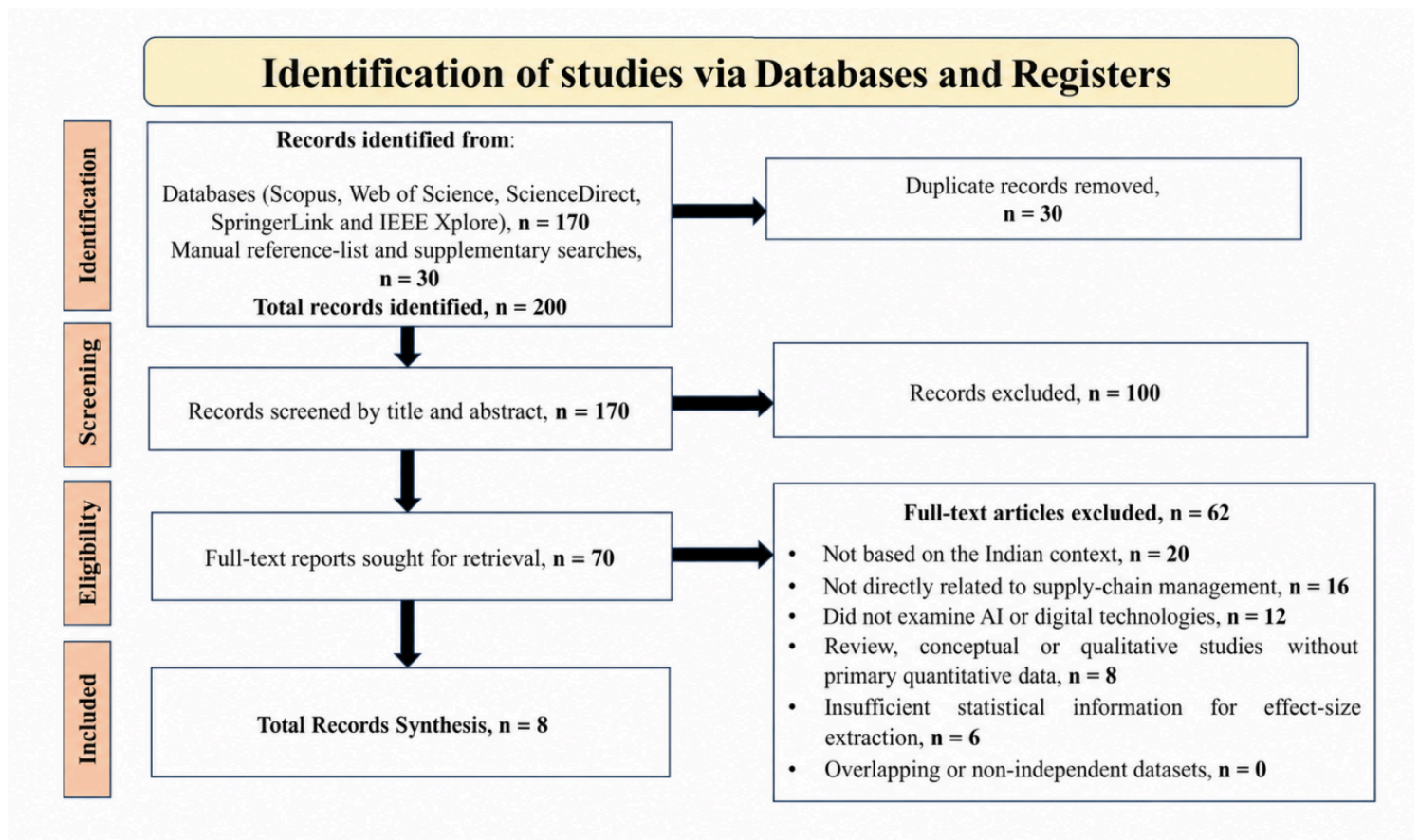


Figure 1

PRISMA flow diagram illustrating identification, screening, eligibility assessment, and final inclusion of eight studies

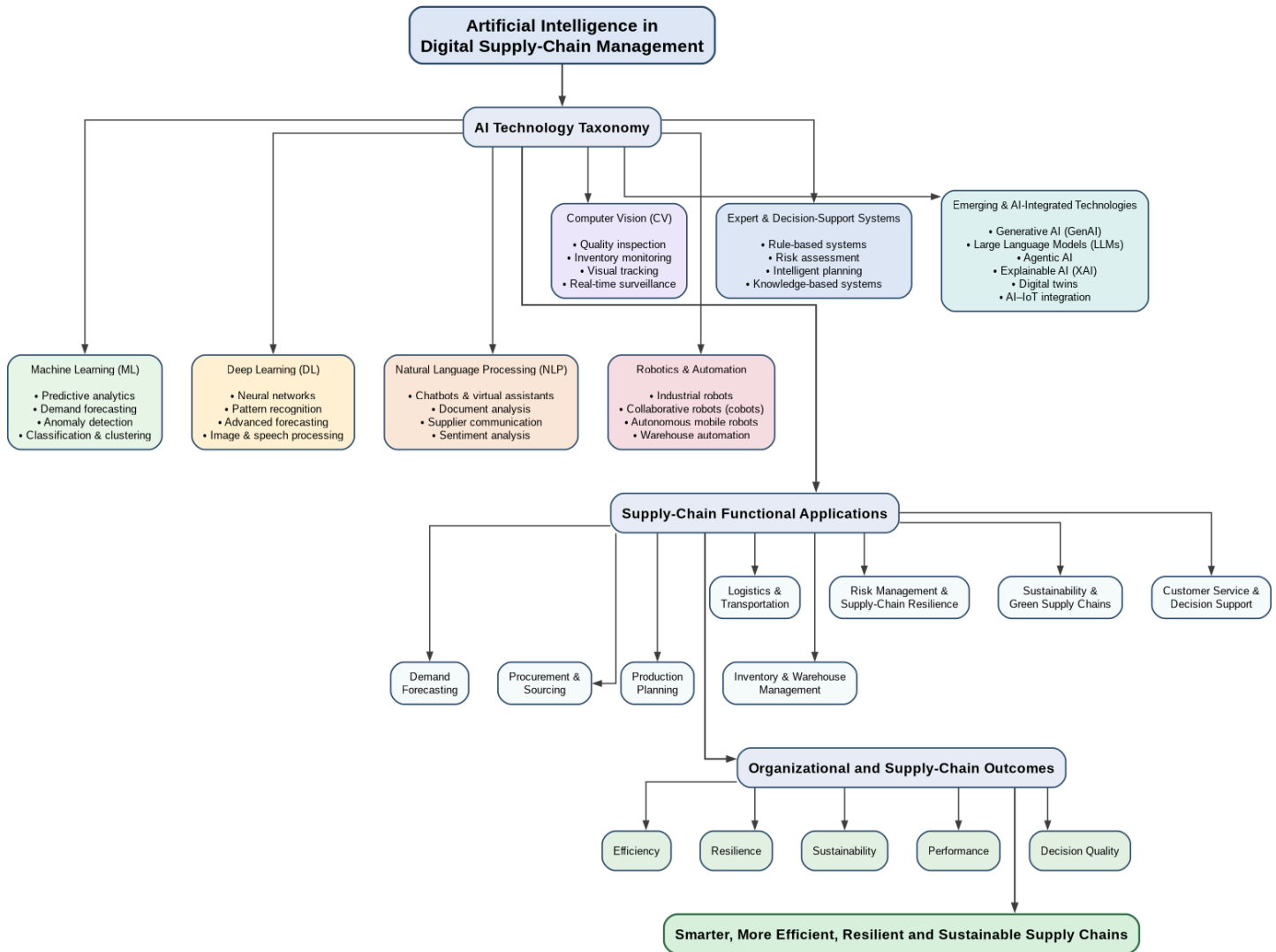


Figure 2

Figure 5. Taxonomy of AI and digital technologies, functional applications, and associated outcomes in digital supply-chain management

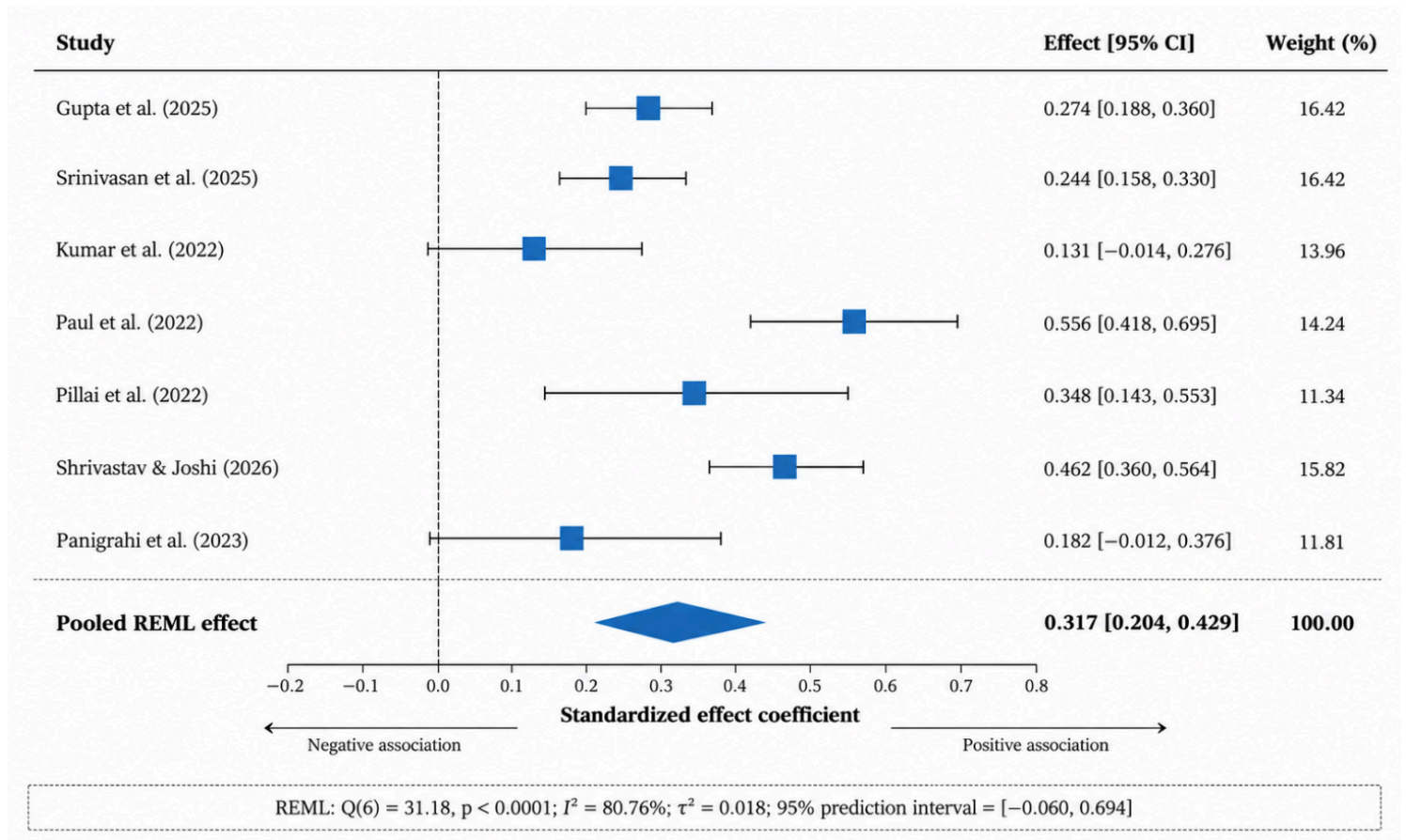


Figure 3

Figure 2. Forest plot of seven standardised study effects with 95% confidence intervals, random-effects weights, and the REML pooled estimate

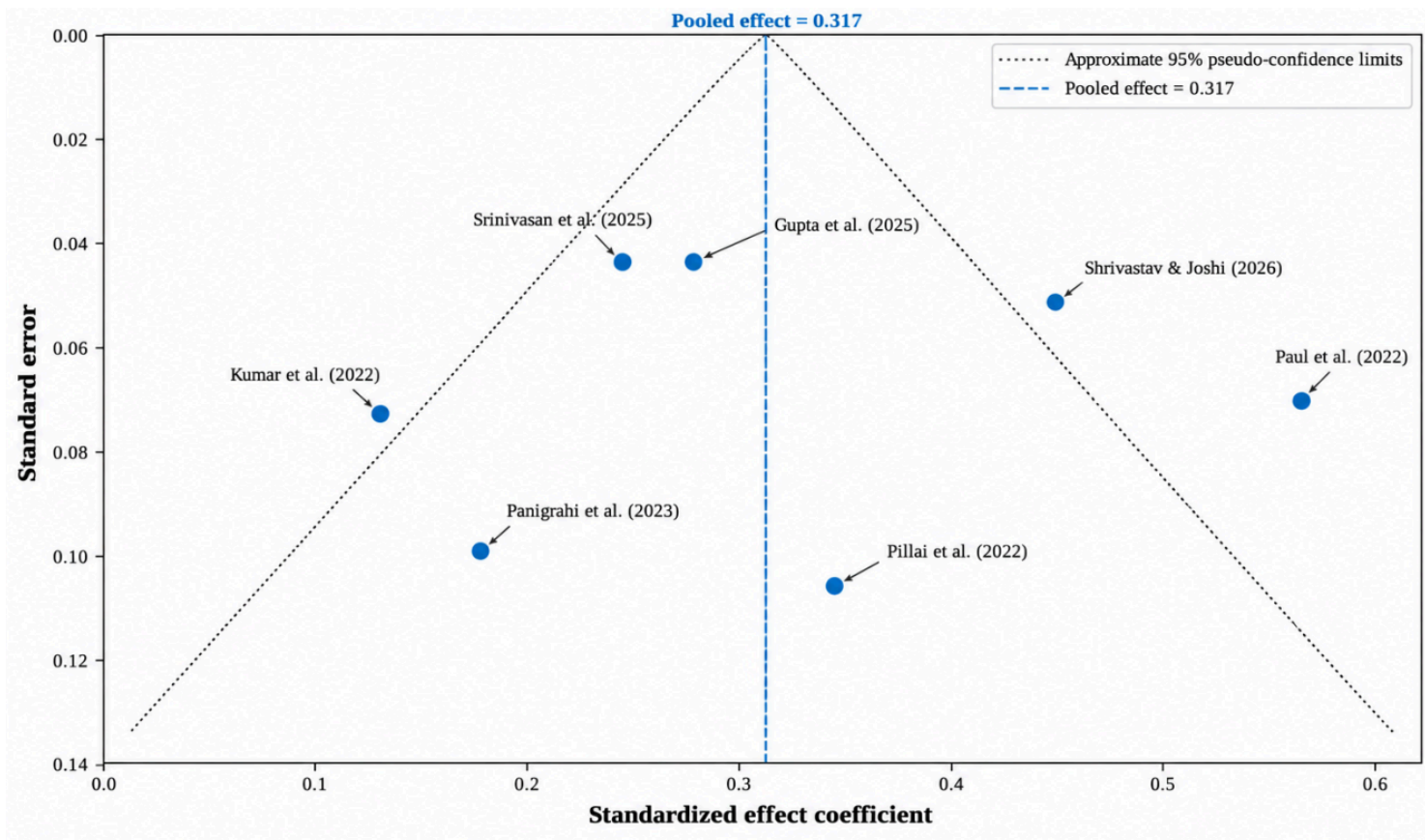


Figure 4

Figure 3. Funnel plot of standardised effect estimates against standard errors for assessment of small-study asymmetry in the primary meta-analysis

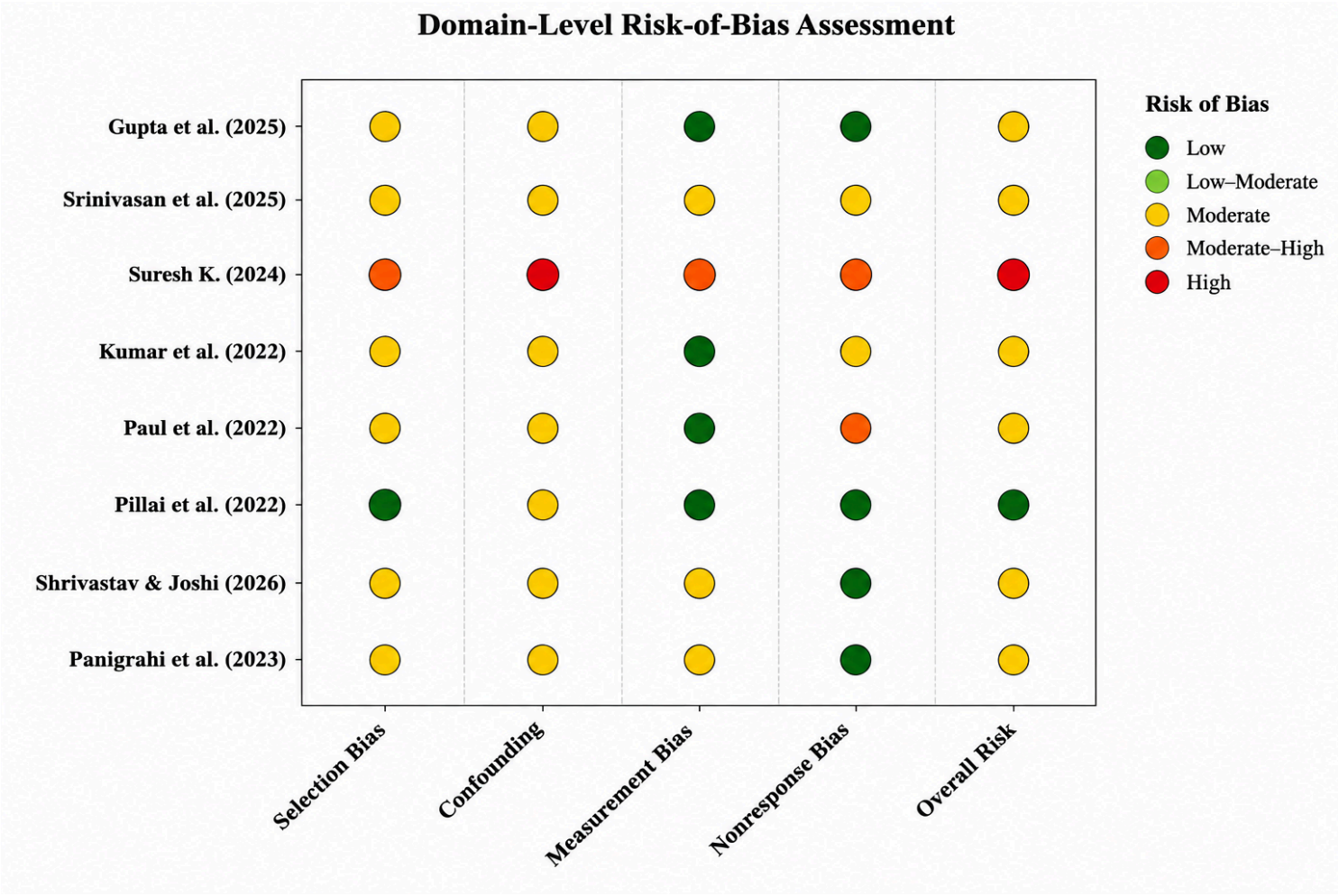


Figure 5

Figure 4. Traffic-light visualisation of selection, confounding, measurement, nonresponse, and overall risk-of-bias ratings across the eight included studies

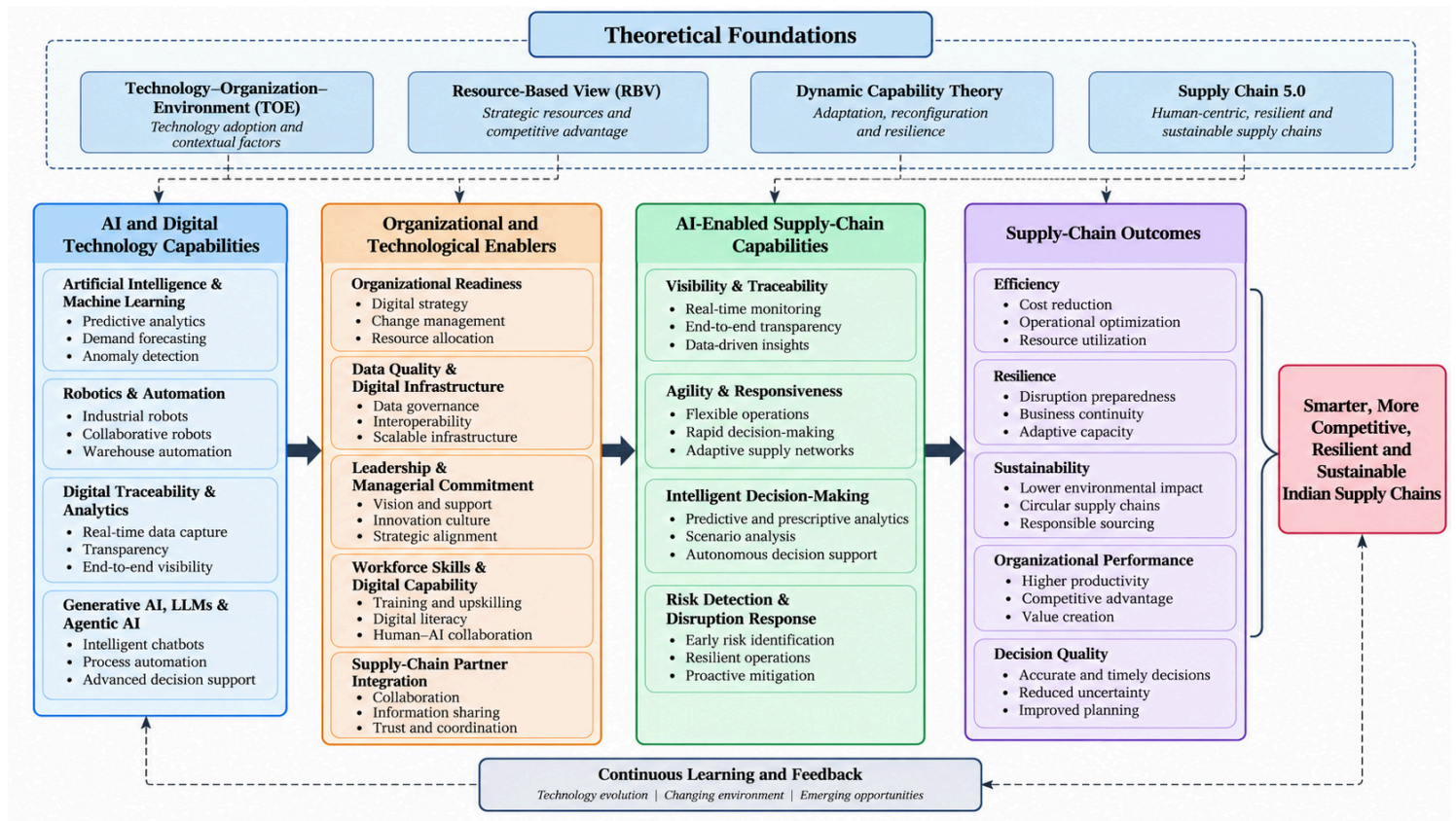


Figure 6

Figure 6. Conceptual framework linking AI and digital technology capabilities, organizational enablers, AI-enabled supply-chain capabilities, and supply-chain outcomes

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