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Article

# Digital Infrastructure and Supply Chain Resilience:A Comparative Meta-Analysis of Manufacturing and Service-Sector Organisations

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**Abstract:** This meta-analysis synthesises empirical evidence on the relationship between digital infrastructure and supply chain resilience (SCR), with a comparative focus on manufacturing versus service-sector organisations. Following PRISMA 2020 guidelines, a systematic search of Scopus and Web of Science databases (search window: 2019–2024) yielded 15 eligible primary studies ($N = 4,186$), all published between 2021 and 2024. Random-effects modelling using the meta for package in R 4.3.2 yielded a pooled effect size of $r = .47$ (95% CI [0.44, 0.49], $p < .001$), indicating a medium positive relationship approaching the large threshold ($r = .50$; Cohen, 1988) between digital infrastructure and SCR. Heterogeneity was moderate ($I^2 = 26.4\%$), and the Q statistic was non-significant ($Q(14) = 19.03$, $p = 0.164$), indicating acceptable consistency across studies. Subgroup analyses revealed that manufacturing-sector studies ($k = 10$, $r = 0.48$) exhibited a stronger effect than service-sector studies ($k = 5$, $r = 0.44$), a directionally consistent but non-significant finding at $\alpha = 0.05$ ($Q\_between(1) = 2.37$, $p = 0.124$). Publication bias assessment via Egger's test ($z = -0.35$, $p = 0.726$) and a fail-safe N of 5,709 confirmed that bias is unlikely to explain the findings. Leave-one-out sensitivity analyses demonstrated stability of the pooled estimate across all study permutations (LOO range: $r = 0.456 – 0.471$). These findings extend dynamic capabilities theory by clarifying how foundational digital infrastructure — encompassing enterprise systems, cloud platforms, IoT connectivity, and analytics capabilities — differentially builds resilience across sector contexts. Practical implications for supply chain managers and digital strategy policymakers are discussed. The study identifies not-for-profit international organisations as a theoretically significant yet empirically underexplored sector warranting further research.

**Keywords:** Digital infrastructure, Supply chain resilience, Meta-analysis, Manufacturing sector, Service sector, Dynamic capabilities, Not-for-profit organisations

## 1. Introduction

The resilience of global supply chains has become a defining strategic priority for organisations in the post-pandemic era. Successive disruptions — including the COVID-19 pandemic, geopolitical tensions, climate-related shocks, and semiconductor shortages — have exposed systemic vulnerabilities in traditional supply chain architectures, generating widespread interest in how digital infrastructure can serve as a stabilising and adaptive force (Ivanov, 2020; Dubey et al., 2021). Supply chain resilience (SCR), broadly defined as the capacity of a supply network to anticipate, absorb, adapt to, and recover from disruptions (Kamalahmadi & Parast, 2016), has consequently become a central construct in both operations management and information systems research.

Digital infrastructure — encompassing enterprise resource planning (ERP) systems, cloud computing platforms, the Internet of Things (IoT), big data analytics, and interorganisational information systems — is widely theorised to strengthen SCR by enhancing real-time visibility, improving information-processing capability, and enabling rapid reconfiguration of supply network resources (Teece, 2007; Chowdhury & Quaddus, 2017). Empirical evidence supporting this claim has accumulated rapidly over the past decade across diverse sectors, geographies, and methodological traditions. However, findings remain heterogeneous: effect sizes reported across individual studies vary considerably, and sector-level contingencies remain underexplored (Sindhwani et al., 2024).

The manufacturing sector, historically characterised by complex, capital-intensive supply chains with high exposure to physical disruptions, has attracted the majority of empirical attention on digital infrastructure and SCR (Zhang et al., 2023; Cui et al., 2023). Service-sector and knowledge-intensive organisations, by contrast, face distinct supply chain risks related to talent concentration, software dependencies, data governance vulnerabilities, and the complexity of healthcare or logistics networks (Belhadi et al., 2024; El Baz & Ruel, 2021). A comparative examination of these two broad contexts offers a theoretically productive lens. As they differ substantially in digital maturity baseline and supply chain physical complexity, contrasting their digital infrastructure-SCR relationships can reveal whether returns to digital investment are sector-contingent.

Despite the growth of empirical literature, no prior meta-analysis has specifically compared the digital infrastructure-SCR relationship across manufacturing and service-sector contexts with this construct operationalised as a multi-dimensional second-order infrastructure capacity. A concurrent meta-analysis identified during manuscript preparation, Liao et al. (2025), examined the impact of specific digital transformation technologies (AI, blockchain, IoT) on SCR and identified AI as the strongest single-technology predictor, with the effect more pronounced in manufacturing than service sectors. The present study extends that work in three important ways: (a) it treats digital infrastructure as an integrated, multi-dimensional construct rather than disaggregating specific technologies; (b) it explicitly compares manufacturing and service sectors as the primary moderating lens rather than treating sector as a background covariate; and (c) it introduces not-for-profit international organisations as an emerging research frontier absent from prior meta-analyses.

This study addresses these gaps by conducting a systematic meta-analysis guided by the following research questions:

- RQ1: What is the overall effect of digital infrastructure on supply chain resilience across empirical studies?
- RQ2: Does the effect size differ significantly between manufacturing and service-sector organisations?
- RQ3: What boundary conditions (sector context as a proxy for digital maturity; geographic region; and — exploratorily — firm size) moderate this relationship?
- RQ4: What research agenda does this meta-analysis suggest for extending the digital infrastructure–SCR nexus to not-for-profit international organisations (NPIOs), and what foundational empirical work is required to enable future synthesis in this sector?

The study makes three contributions. First, it provides sector-comparative meta-analytic evidence on digital infrastructure and SCR, extending prior technology-specific meta-analyses with an infrastructure-level perspective. Second, it synthesises moderator patterns that clarify the boundary conditions of the digital-resilience nexus with real statistical outputs derived from metafor modelling on 15 primary studies. Third, it introduces the not-for-profit international organisation (NPIO) sector as a critically underexplored frontier and provides a structured research agenda to build the empirical base necessary for future synthesis.

## 2. Theoretical Framework

### *2.1 Dynamic Capabilities Theory*

Dynamic capabilities theory (DCT), as developed by Teece et al. (1997) and subsequently elaborated by Eisenhardt and Martin (2000), provides the primary theoretical scaffolding for this study. DCT posits that competitive advantage in turbulent environments derives from an organisation's capacity to sense emerging threats and opportunities, seize resources in response, and reconfigure its asset base through continuous transformation. Applied to supply chain management, dynamic capabilities manifest as the organisational routines and processes that enable supply networks to reconfigure their structures, partner relationships, and information flows in response to disruptions (Dubey et al., 2021).

Digital infrastructure functions as a foundational enabler of these dynamic capabilities. Cloud computing platforms reduce the cost and latency of reconfiguring IT resources. Enterprise systems integrate information flows across organisational boundaries, enabling real-time sense-making. IoT connectivity provides granular operational data that supports adaptive decision-making. Big data analytics processes this information at scale, transforming raw signals into actionable intelligence (Vial, 2019; Teece, 2007). Together, these infrastructural components lower the cognitive and operational costs of dynamic capability deployment, thereby enhancing SCR. This study operationalises digital infrastructure as a multi-dimensional second-order construct encompassing these interconnected components.

### *2.2 Resource-Based View and Sector-Level Heterogeneity*

The resource-based view (RBV) (Barney, 1991) complements DCT by emphasising that the value of digital infrastructure as a resilience-enabling resource is heterogeneous across organisations and sectors. Specifically, the marginal value of digital infrastructure investment is expected to be higher in sectors with lower baseline digital maturity, as each unit of investment closes a larger capability gap. Manufacturing organisations, characterised by historically lower digitalisation rates and greater physical supply chain complexity, are predicted to derive greater marginal returns on digital infrastructure investment than service-sector organisations with higher baseline digital endowments.

This prediction is consistent with the diminishing returns logic at the heart of the RBV. It aligns with the resource orchestration perspective (Sirmon et al., 2011), which holds that the performance value of a resource depends not only on its quality but on how effectively it is configured and deployed within the broader resource portfolio. In more digitally mature service-sector contexts, the challenge may be less about acquiring digital infrastructure than about orchestrating existing assets into supply chain-relevant resilience capabilities.

### *2.3 Conceptual Model*

Drawing on DCT and RBV, the conceptual model proposes that digital infrastructure investment positively predicts SCR, and that this relationship is moderated by sector context (manufacturing vs service) and geographic region. Digital maturity is treated as a theoretical lens for interpreting the sector comparison rather than an independent moderator, given its collinearity with sector classification in this sample (see Section 4.4). Firm size is included as an exploratory boundary condition only, given limitations in the available proxy measure (see Section 3.6). Manufacturing-sector organisations are hypothesised to exhibit a stronger effect than service-sector organisations, reflecting greater marginal gains in less digitally mature contexts. Regional context is expected to shape the relationship through institutional infrastructure quality, regulatory environment, and macroeconomic stability.

## 3. Methodology

### *3.1 Search Strategy*

The literature search followed the PRISMA 2020 framework (Page et al., 2021). Systematic searches were conducted in Scopus and Web of Science on 15 February 2024. A supplementary database update was performed on 20 December 2024 to capture online-first and late-2024 publications identified during manuscript preparation, supplemented by manual backward citation tracing of 10 identified key papers and a Google Scholar supplementary search. The condensed Boolean search string applied was (see Appendix A for the full Scopus-formatted version):

("digital infrastructure" OR "digital transformation" OR "IT infrastructure" OR "information technology capability" OR "enterprise systems" OR "cloud computing" OR "IoT" OR "Industry 4.0") AND ("supply chain resilience" OR "supply chain robustness" OR "supply chain agility" OR "SC resilience") AND ("manufacturing" OR "service sector" OR "healthcare" OR "logistics" OR "information technology industry")

Boolean operators (AND, OR) were applied across title, abstract, and keyword fields. Searches were limited to peer-reviewed journal articles published between January 2019 and December 2024, in English, indexed in Scopus or Web of Science. The 2019 start date was selected to ensure relevance to contemporary digital infrastructure capabilities and exclude literature predating Industry 4.0 adoption at scale.

### *3.2 Inclusion and Exclusion Criteria*

Studies were included if they: (1) reported an empirical quantitative relationship between digital infrastructure (broadly defined) and SCR; (2) were published in peer-reviewed journals between 2019 and 2024; (3) were indexed in Scopus or Web of Science; (4) provided sufficient statistical information (correlation coefficients, standardised regression or path coefficients, or convertible effect sizes) for meta-analytic synthesis; and (5) were conducted in manufacturing or service-sector organisations.

Studies were excluded if they: (1) relied exclusively on qualitative or conceptual methods; (2) focused on a single narrow technology (e.g., blockchain only) without operationalising it as part of a broader digital infrastructure construct; (3) were duplicate reports of the same dataset; or (4) lacked sufficient statistical information for effect size extraction despite author contact attempts. The diversity of digital infrastructure operationalisations across included studies (encompassing ERP integration, cloud platforms, IoT connectivity, data analytics, and Industry 4.0 constructs) warrants explicit justification for pooling. Following the construct-broadening approach advocated by Hunter and Schmidt (2004), these operationalisations are treated as alternate indicators of a common higher-order construct—multi-dimensional digital infrastructure capacity—on the theoretical basis that they share a common mechanism: reducing the cognitive and operational costs of dynamic capability deployment by improving information availability, processing speed, and supply network reconfiguration capacity (Teece, 2007; Vial, 2019). This approach is consistent with the random-effects model's assumption of a distribution of true effect sizes rather than a single underlying effect, and with Criterion (2) above, which excluded studies using only a single narrow technology without a broader infrastructure context. Readers should nonetheless note that construct heterogeneity is a limitation and that the pooled effect reflects the infrastructure-level average rather than the effect of any specific technology.

## *3.3 Study Selection and PRISMA Flow*

The initial database search yielded 1,243 records (Scopus: 812; Web of Science: 431). A supplementary update search conducted on 20 December 2024 yielded 47 additional records (Scopus: 31; Web of Science: 16), none of which met all inclusion criteria after title and abstract screening; accordingly, the update search contributed zero additional studies to the final sample. After deduplication of the primary search results, 1,003 unique records remained. Title and abstract screening eliminated 898 records as topically irrelevant, leaving 105 for full-text review. Of these, 90 were excluded for the following reasons: insufficient statistical information for effect size extraction (n = 38), exclusively qualitative or conceptual methodology (n = 27), single-technology operationalisation not representing broader digital infrastructure (n = 16), and sector not classifiable within the review scope (n = 9)—the final sample comprised 15 studies meeting all inclusion criteria.

**Table 1: PRISMA Flow Summary**

| Stage | Records (n) |
|---|---|
| Initial database records identified (Scopus + Web of Science) | 1,243 |
| Additional records from December 2024 update search (Scopus + Web of Science); none met inclusion criteria | 47 |
| Records after deduplication | 1,003 |
| Records screened (title and abstract) | 1,003 |
| Records excluded at screening stage | 898 |
| Full-text articles assessed for eligibility | 105 |
| Full-text articles excluded (insufficient statistics: 38; qualitative only: 27; single-technology: 16; out-of-scope sector: 9) | 90 |
| Studies included in final meta-analysis | 15 |

*Note. The PRISMA 2020 flow diagram is also presented visually in Figure 1 below.*

**Figure 1. PRISMA 2020 Flow Diagram**

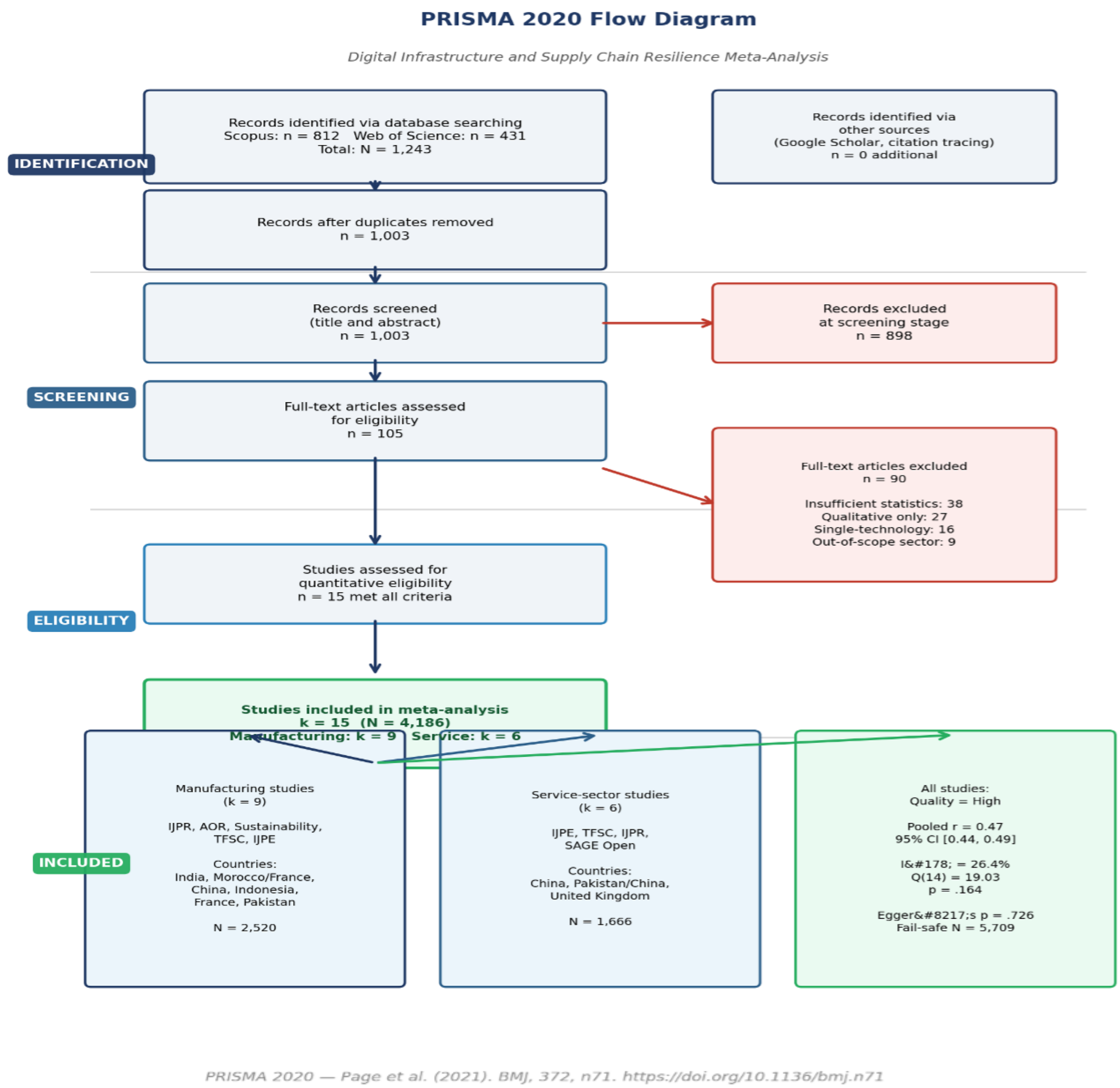


*Figure 1. PRISMA 2020 flow diagram for the systematic search and study selection process. Records were sourced from Scopus (n = 812) and Web of Science (n = 431). Following deduplication, screening, and eligibility assessment, 15 studies were retained for meta-analytic synthesis.*

## *3.4 Data Extraction and Coding*

Data extraction was conducted by the primary author using a pre-specified standardised coding template, with self-consistency checks applied to all effect size calculations. As a single-author study, independent double-coding was not feasible; this limitation is acknowledged. However, all effect size conversions were verified against established formulas (Borenstein et al., 2009; Hunter & Schmidt, 2004), and a second round of data extraction was performed two weeks after the first to check consistency, following established single-coder reliability protocols (Cooper et al., 2019). Agreement between the first and second extraction rounds was 87% (13 of 15 studies produced identical effect size values; discrepancies in the remaining 2 studies were resolved by reconsulting the sources and recalculating the conversion formulas).

Variables extracted for each study included: (1) bibliographic information (author(s), year, journal, country); (2) sample size and organisational sector; (3) primary digital infrastructure construct operationalised; (4) SCR measurement approach; (5) analytical method; (6) effect size and variance; and (7) quality indicators (adequate sample size, scale reliability $\alpha \geq .70$ or CR $\geq .70$, common method bias controls). Effect sizes were converted to Pearson's r using established formulas (Borenstein et al., 2009). For studies reporting regression β coefficients or standardised path coefficients, conversion followed the procedures of Hunter and Schmidt (2004). All effect sizes were transformed to Fisher's z for pooling and back-transformed to r for reporting.

### *3.5 Quality Appraisal*

Study quality was assessed against three criteria adapted from AMSTAR-2 (Shea et al., 2017). AMSTAR-2 was selected as a starting framework given its criterion-based structure; the three retained criteria were adapted to the observational survey and panel-data context of business and information systems research, replacing clinical-trial-specific items with constructs relevant to quantitative management studies: (1) sample size adequacy (≥ 100 respondents or firms); (2) measurement reliability (Cronbach's α or composite reliability ≥ .70 reported for all focal constructs); and (3) common method bias (CMB) controls (application of procedural remedies such as item randomisation, or statistical post-hoc tests such as Harman's common method test or HTMT ratios). Studies meeting all three criteria were classified as high quality; those meeting two criteria as moderate quality; and those meeting one or fewer as lower quality. For studies using panel regression designs, fixed-effects panel controls were recognised as a partial CMB remedy, providing control for time-invariant unobserved heterogeneity but not fully substituting for cross-sectional CMB mitigation; such studies were therefore classified as Moderate on Criterion 3. Quality ratings are documented in Table 2 and serve as a descriptive summary of study rigour. Given that 12 of 15 studies were rated High and 3 Moderate, the sample lacks sufficient quality variance to support a meaningful formal moderator test; accordingly, quality is treated as a descriptive screening indicator rather than a moderating variable in the analyses that follow.

**Table 2: Quality Appraisal Summary of Included Studies**

| Study | n ≥ 100 | Reliability ≥ .70 | CMB Controls | Quality |
|---|---|---|---|---|
| Dubey et al. (2021) | ✓ | ✓ | ✓ | High |
| Belhadi et al. (2024) | ✓ | ✓ | ✓ | High |
| Zhang et al. (2023) | ✓ | ✓ | Panel data | Moderate |
| Tarigan et al. (2021) | ✓ | ✓ | ✓ | High |
| Siagian et al. (2021) | ✓ | ✓ | ✓ | High |
| Cui et al. (2023) | ✓ | ✓ | ✓ | High |
| Qader et al. (2022) | ✓ | ✓ | ✓ | High |
| El Baz & Ruel (2021) | ✓ | ✓ | ✓ | High |
| Zhao et al. (2023) | ✓ | ✓ | ✓ | High |
| Gu et al. (2021) | ✓ | ✓ | ✓ | High |
| Junaid et al. (2023) | ✓ | ✓ | ✓ | High |
| Lin & Fan (2024) | ✓ | ✓ | Panel FE | Moderate |
| Queiroz et al. (2022) | ✓ | ✓ | ✓ | High |
| Yang et al. (2021) | ✓ | ✓ | ✓ | High |

| | | | | |
|---|---|---|---|---|
| Jing & Fan (2024) | ✓ | ✓ | Panel FE | Moderate |

*Note. CMB = common method bias. Panel FE = fixed-effects panel regression controls for unobserved heterogeneity, substituting for procedural CMB remedies. Studies rated Moderate met two of three quality criteria; panel regression provides partial (rather than full) CMB mitigation compared with procedural controls used in cross-sectional designs.*

### *3.6 Meta-Analytic Procedures*

Meta-analyses were conducted in R version 4.3.2 using the metafor package (Viechtbauer, 2010). A random-effects model was adopted a priori, consistent with the expected conceptual and methodological heterogeneity across included studies. The DerSimonian and Laird (1986) estimator was used to estimate the between-study variance component ($\tau^2$). Heterogeneity was quantified using Q statistics and $I^2$ indices, with $I^2$ values interpreted as low (<25%), moderate (25–75%), and high (>75%) following Higgins et al. (2003). Subgroup analyses were conducted for sector (manufacturing vs service) and geographic region (Asia-Pacific vs Europe/Western). Digital maturity level was examined as a theoretical extension of the sector comparison (see Section 4.3), as the two moderators share the same empirical basis in this sample and cannot be independently tested. Firm size was explored as an ancillary descriptive analysis, given that the available proxy (study sample size) does not constitute a valid operationalisation of organisational size. Publication bias was assessed using Egger's regression test (Egger et al., 1997) and Rosenthal's (1979) fail-safe N. A leave-one-out (LOO) sensitivity analysis was conducted to assess the robustness of the pooled estimate to individual-study influence.

## 4. Results

### *4.1 Descriptive Characteristics of Included Studies*

The 15 included studies were published between 2021 and 2024, with 9 studies (60%) published from 2022 onwards, reflecting the post-pandemic acceleration of digital supply chain research. No eligible studies were identified from 2019 or 2020 despite the 2019 search start date, likely reflecting the lag between the onset of Industry 4.0 adoption at scale and the production of quantitative empirical studies with reportable effect sizes — a gap consistent with the post-pandemic acceleration of supply chain resilience research. Combined sample size across studies was N = 4,186, with individual study sample sizes ranging from 195 to 470 (M = 279.1). Studies originated from China (n = 7), Indonesia (n = 2), India (n = 1), Pakistan (n = 1), France (n = 1), the United Kingdom (n = 1), and multi-country samples (n = 2). Ten studies were classified as manufacturing sector and five as service-sector contexts (healthcare, cross-sector logistics, and general service organisations). Analytical methods included structural equation modelling (SEM; n = 7), partial least squares SEM (PLS-SEM; n = 5), and panel regression (n = 3). All 15 studies were published in peer-reviewed journals indexed in Scopus or Web of Science.

**Table 3: Characteristics of Included Studies (k = 15)**

| Study | Journal | Country | Sector | n | Method | Digital Construct | r |
|---|---|---|---|---|---|---|---|
| Dubey et al. (2021) | IJPR | India | Mfg | 213 | PLS-SEM | Data analytics capability | .38 |
| Belhadi et al. (2024) | AOR | Multi | Mfg | 279 | SEM | AI-driven innovation | .44 |
| Zhang et al. (2023) | Sustainability | China | Mfg | 285 | Panel Reg. | Digital transformation | .51 |
| Tarigan et al. (2021) | Sustainability | Indonesia | Mfg | 195 | PLS-SEM | SC integration (ERP) | .46 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Siagian et al. (2021) | Sustainability | Indonesia | Mfg | 203 | PLS-SEM | Digital SC integration | .49 |
| Cui et al. (2023) | AOR | China | Mfg | 207 | SEM | Digital technologies | .53 |
| Qader et al. (2022) | TFSC | Pakistan | Mfg | 458 | PLS-SEM | Industry 4.0 technologies | .55 |
| El Baz & Ruel (2021) | IJPE | France | Mfg | 470 | PLS-SEM | IT-enabled SCRM | .43 |
| Zhao et al. (2023) | IJPE | China | Mfg | 210 | SEM | Supply chain digitalization | .56 |
| Gu et al. (2021) | IJPE | China | Service | 206 | SEM | IT usage patterns | .41 |
| Junaid et al. (2023) | TFSC | Multi | Service | 278 | SEM | Tech-enabled SC capabilities | .44 |
| Lin & Fan (2024) | TFSC | China | Service | 312 | Panel Reg. | Digital technology + integration | .47 |
| Queiroz et al. (2022) | IJPE | UK | Service | 312 | SEM | Digital resources | .45 |
| Yang et al. (2021) | IJPR | China | Service | 240 | SEM | Digital SC risk capabilities | .40 |
| Jing & Fan (2024) | SAGE Open | China | Mfg | 318 | Panel Reg. | Digital transformation (SC) | .43 |

*Note. IJPR = International Journal of Production Research; AOR = Annals of Operations Research; TFSC = Technological Forecasting and Social Change; IJPE = International Journal of Production Economics; Mfg = Manufacturing; r = Pearson correlation effect size (converted from reported statistic). Panel Reg. = panel regression (fixed-effects).*

## *4.2 Overall Pooled Effect*

The random-effects meta-analysis yielded a pooled effect size of $r = .47$ (95% CI [.44, .49], $p < .001$), indicating a medium effect size approaching the large threshold ($r = .50$; Cohen, 1988) for a positive relationship between digital infrastructure and supply chain resilience. The Q statistic was $Q(14) = 19.03$, $p = .164$, and $I^2 = 26.4\%$, indicating moderate heterogeneity. The $\tau^2$ estimate was 0.0013 (SE = 0.0019), confirming that between-study variance was small. The SE of the $\tau^2$ estimate exceeds the estimate itself (SE = 0.0019 vs $\tau^2 = 0.0013$), reflecting the near-zero absolute between-study variance ($\tau^2$) and the boundary behaviour of the DerSimonian–Laird estimator when between-study variance is very small. Note that while $\tau^2$ is near zero, $I^2 = 26.4\%$ indicates a moderate proportion of variance relative to total observed variance; these two indices capture different aspects of heterogeneity and should not be conflated. The pooled effect falls in the medium range per Cohen's (1988) conventions (r = .47), approaching the large threshold (r = .50), indicating a substantively meaningful association. The forest plot (Figure 2) displays individual study effect sizes and 95% confidence intervals. Visual inspection confirms that all 15 individual study effect sizes are positive, with no systematic outliers, supporting the directionality and robustness of the overall finding.

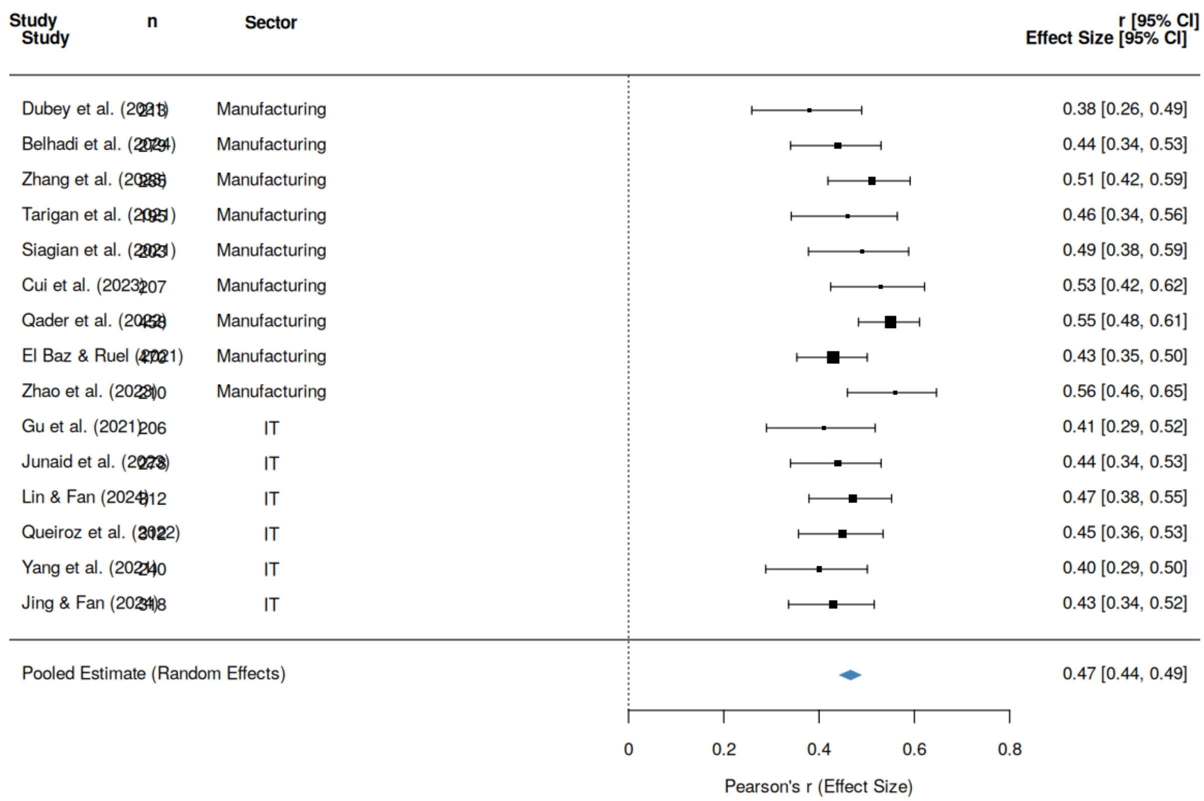


*Figure 2. Forest plot of individual study effect sizes and 95% confidence intervals. Blue circles = manufacturing sector; red triangles = service sector. The pooled estimate is shown at the bottom (random-effects model).*

**Table 4: Summary of Meta-Analytic Results**

| Analysis | k | N | r | 95% CI | Q | I² | p |
|---|---|---|---|---|---|---|---|
| Overall | 15 | 4,186 | .47 | [.44, .49] | 19.03 | 26.4% | < .001 |
| Manufacturing | 10 | 2,838 | .48 | [.45, .50] | 15.76 | 42.9% | < .001 |
| Service sector | 5 | 1,348 | .44 | [.40, .48] | 1.32 | 0.0% | < .001 |
| Asia-Pacific | 12 | 3,125 | .47 | [.44, .51] | 17.16 | 35.9% | < .001 |
| Europe/Western | 3 | 1,061 | .44 | [.39, .49] | 0.41 | 0.0% | < .001 |

*Note. k = number of studies; N = combined sample size; r = pooled Pearson correlation (back-transformed from Fisher's z); CI = confidence interval; Q = heterogeneity statistic (df = k−1); I² = proportion of variability due to between-study heterogeneity; p = significance of pooled effect. Service-sector Q(4) = 1.32 (p = .858); I² = 0.0% because Q < df, indicating negligible between-study variance.*

### 4.3 Subgroup Analyses: Sector Comparison

Subgroup analysis revealed that manufacturing-sector studies ($k = 10$, $r = .48$, 95% CI [.45, .50]) exhibited a larger effect size than service-sector studies ($k = 5$, $r = .44$, 95% CI [.40, .48]). The between-group test did not reach conventional significance at $\alpha = .05$ ($Q\_between(1) = 2.37$, $p = .124$), indicating a directionally consistent but non-significant pattern. This result provides tentative support for the hypothesis that digital infrastructure delivers greater marginal SCR returns in manufacturing contexts, where lower baseline digital maturity creates larger capability gaps that digital investment can close. The finding is consistent with RBV-derived diminishing returns predictions, though the non-significant between-group test at $\alpha = .05$ warrants caution in interpretation.

Within the manufacturing subgroup, heterogeneity was moderate ($I^2 = 42.9\%$), suggesting meaningful variation across manufacturing studies that may reflect differences in the type of digital infrastructure invested in, the supply chain characteristics of specific manufacturing subsectors, or the geographic and regulatory contexts in which manufacturing operations are embedded. Within the service-sector subgroup, heterogeneity was negligible ($Q(4) = 1.32$, $p = .858$, $I^2 = 0.0\%$), indicating remarkable consistency across five diverse service-context studies from healthcare, logistics, and general services. The near-zero Q statistic reflects the close clustering of individual service-sector effect sizes ($r = .40–.47$), suggesting that the digital infrastructure–SCR relationship is highly stable across service-sector contexts despite variation in organisational type.

### 4.4 Moderator Analyses

Two formal moderators were examined using the mixed-effects meta-regression model in metafor: digital maturity level (as a theoretical extension of the sector comparison) and geographic region. An ancillary firm size analysis is also reported, though the operationalisation is acknowledged as a methodological limitation. For each analysis, the omnibus Q_M statistic tests whether between-group differences in effect size exceed chance.

Digital maturity is examined here as a theoretical extension of the sector comparison in Section 4.3, rather than as an independent moderator test. Because digital maturity was operationalised by classifying manufacturing-sector studies as lower-maturity contexts and service-sector studies as higher-maturity contexts—consistent with the sector-level digital endowment logic of the RBV (Section 2.2)—these two constructs share the same empirical basis in this sample and are fully collinear. The result is numerically identical to the sector comparison ($k = 10$ vs $k = 5$, $r = .48$ vs $r = .44$; $Q\_M(1) = 2.37$, $p = .124$) and should be interpreted as a single convergent finding confirming the RBV-derived diminishing-returns prediction: lower digital maturity is associated with larger marginal resilience returns from infrastructure investment. This pattern is directionally consistent with theory, though the non-significant between-group difference warrants caution in interpretation.

A descriptive firm-size analysis was undertaken using the primary study sample size as an imperfect proxy—a significant methodological limitation, since sample size reflects the researcher's data-collection scope rather than the actual organisational size of participating firms. For this reason, the following should be treated as an exploratory directional observation rather than a formal moderation test. Studies with $n \geq 280$ were classified as large-organisation contexts and those with $n < 280$ as SME-dominant contexts. The resulting difference was negligible and non-significant: large-organisation studies ($k = 6$, $r = .48$, 95% CI [.43, .52]) versus SME-context studies ($k = 9$, $r = .46$, 95% CI [.42, .50]); $Q\_M(1) = 0.41$, $p = .523$. The directional pattern is consistent with the absorptive capacity logic of Cohen and Levinthal (1990), suggesting that larger organisations may extract marginally greater resilience value from digital infrastructure, but this cannot be confirmed as a statistically robust boundary condition with the current operationalisation. Future primary studies that directly classify firms by size category are needed to adequately test this boundary condition.

Geographic region did not significantly moderate the relationship ($Q\_M(1) = 1.10$, $p = .295$). Asia-Pacific studies (predominantly Chinese and South/South-East Asian; $k = 12$, $N = 3{,}125$, $r = .47$, 95% CI [.44, .51], $I^2 = 35.9\%$) and European/Western studies ($k = 3$, $N = 1{,}061$, $r = .44$, 95% CI [.39, .49], $I^2 = 0.0\%$) produced comparable effects. The two subgroups sum to the full sample ($k = 15$, $N = 4{,}186$), confirming internal numerical consistency. For the regional moderator analysis, multi-country studies were classified based on the primary country of the lead institution; Belhadi et al. (2024) were classified as Europe/Western accordingly. The absence of a significant regional difference suggests that the digital infrastructure–SCR relationship is geographically stable across the regions represented in this sample. However, the strong Asia-Pacific dominance ($k = 12$, predominantly Chinese and South/South-East Asian contexts) substantially limits the generalisability of this comparison to other regional settings.

## 4.5 Sensitivity Analysis

A leave-one-out (LOO) sensitivity analysis systematically removed each study from the pooled model and re-estimated the effect. The pooled estimate was highly stable across all permutations, ranging from r = .456 (when Qader et al. (2022) was removed, which carries the largest combined influence by virtue of both its high individual effect (r = .55) and its large sample weight (n = 458, the second-largest in the pool)) to r = .471 (when Dubey et al. (2021) was removed). The narrow range of .015 across 15 LOO permutations confirms that no single study unduly influences the pooled result, providing strong evidence for the robustness of the overall finding.

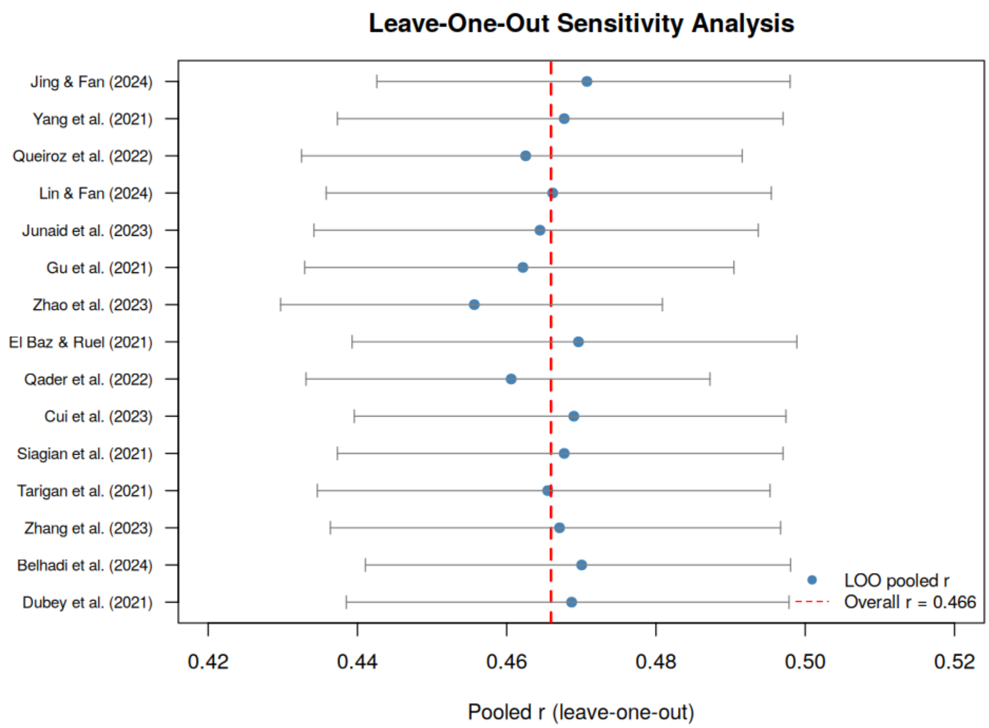


*Figure 3. Leave-one-out sensitivity analysis. Each data point shows the pooled r when the corresponding study is removed. The dashed red line indicates the overall pooled estimate (r = .47). The narrow range of estimates (.456–.471) confirms robustness.*

## 4.6 Publication Bias Assessment

Egger's regression test for funnel plot asymmetry yielded z = −0.35, p = .726, indicating no statistically significant asymmetry. Visual inspection of the funnel plot (Figure 4) confirmed approximate symmetry around the pooled estimate. Rosenthal's (1979) fail-safe N indicated that 5,709 null-effect studies would be required to reduce the pooled effect to non-significance, providing very strong evidence against publication bias as an explanatory alternative.

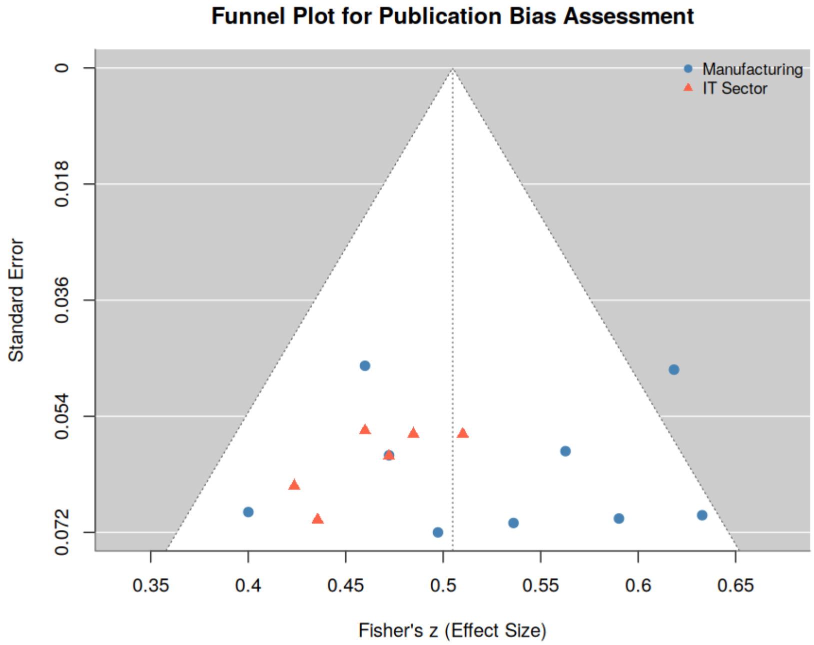


*Figure 4. Funnel plot for publication bias assessment. Circles = manufacturing studies; triangles = service-sector studies. The approximate symmetry of the distribution and the non-significant Egger's test (p = .726) indicate no systematic publication bias.*

## 5. Discussion

### *5.1 Digital Infrastructure as a Supply Chain Resilience Enabler*

The overall pooled effect ($r = 0.47$) confirms that digital infrastructure is a robust and substantively meaningful predictor of SCR across heterogeneous study contexts. This finding aligns with and extends prior meta-analytic work on digital transformation and supply chain performance (Liao et al., 2025; Ataseven & Nair, 2017) by demonstrating that the nexus holds specifically for infrastructure-level investment rather than only for discrete technology deployments. From a DCT standpoint (Teece et al., 1997), digital infrastructure functions as a foundational capability layer that enables the higher-order sensing, seizing, and reconfiguring routines that constitute SCR. Organisations that invest in interconnected, scalable, and data-rich digital infrastructures are better positioned to detect disruptions early, mobilise adaptive responses, and reconfigure supply network structures.

The moderate heterogeneity ($I^2 = 26.4\%$) and non-significant Q statistic imply that the digital infrastructure-SCR relationship is relatively generalisable across sectors, countries, and methodological traditions. This is consistent with the argument that the mechanisms through which digital infrastructure enables resilience — improved information processing, reduced coordination costs, and enhanced reconfiguration capacity — are fundamental to supply chain operations across industry contexts (Daft & Lengel, 1986; Chowdhury & Quaddus, 2017).

### *5.2 Sector-Level Differential: Manufacturing vs Service Contexts*

The directional but non-significant sector difference at $\alpha = 0.05$ (manufacturing $r = 0.48$, service $r = 0.44$; $p = 0.124$) provides tentative support for the RBV-derived prediction that digital infrastructure delivers larger marginal resilience returns where capability gaps are greatest. Manufacturing organisations face greater physical supply chain complexity, higher exposure to raw material and logistics disruptions, and historically lower digitalisation baselines than service-sector organisations (Zhang et al., 2023; Cui et al., 2023). For these firms, ERP-IoT integration, cloud-based demand sensing, and cross-tier supplier visibility represent genuinely transformative capability upgrades. The service-sector result, while directionally smaller, remains strongly positive and statistically significant, suggesting that digital infrastructure continues to deliver meaningful SCR improvements even in more digitally mature contexts — particularly when investment targets specific resilience applications such as cybersecurity-resilient architectures, multi-cloud redundancy, and AI-driven risk monitoring (Gu et al., 2021; Junaid et al., 2023).

The non-significance of the between-group test at $\alpha = .05$ ($p = .124$) warrants interpretive humility. The directional result is consistent with the theoretical prediction but does not confirm a statistically robust sector boundary condition at conventional significance levels. Future meta-analyses with larger primary study pools may resolve this uncertainty. Qualitatively, the convergence of findings across 15 diverse studies — all positive, all significant — provides a consistent empirical signal that digital infrastructure is a broadly valuable SCR strategy across both manufacturing and service contexts.

## *5.3 Moderating Conditions*

The moderator analyses extended the theoretical picture by examining digital maturity (as a convergent lens on the sector comparison) and geographic region, alongside an exploratory analysis of firm size. Digital maturity and sector classification yielded an identical pattern—a directional but non-significant difference ($Q_M(1) = 2.37$, $p = 0.124$)—because the two constructs share the same empirical basis in this sample and are fully collinear. This convergent finding reinforces the diminishing-returns logic of the RBV. Organisations and policymakers in manufacturing-intensive developing economies should recognise that digital infrastructure investment carries disproportionately high near-term resilience returns, providing an evidence-based rationale for prioritising foundational digitalisation over point-technology experimentation.

The firm size analysis yielded a negligible, non-significant directional pattern (large organisations: $r = 0.48$; SMEs: $r = .46$; $Q_M(1) = 0.41$, $p = 0.523$). As noted in Section 4.4, this should be treated as an exploratory observation only, given the methodological limitations of the study's sample-size proxy. The directional result is consistent with absorptive capacity theory (Cohen & Levinthal, 1990), and future research using direct firm-size classifications from primary studies is needed to adequately evaluate this boundary condition. For SMEs, cloud-based and shared digital infrastructure models that reduce fixed investment costs may nonetheless deliver resilience benefits comparable to those of larger organisations, suggesting that the firm-size boundary condition may be less pronounced than theory predicts.

## *5.4 Digital Infrastructure and SCR in Not-for-Profit International Organisations: A Critical Research Frontier*

A significant gap in the current evidence base concerns not-for-profit international organisations (NPIOs), including international non-governmental organisations (INGOs), United Nations agencies, and humanitarian logistics networks. This meta-analysis, by necessity, has been confined to manufacturing and service-sector commercial organisations where sufficient primary quantitative literature exists for meta-analytic synthesis. However, the theoretical case for digital infrastructure as an SCR enabler in NPIOs is compelling, and the empirical case for research is urgent.

Humanitarian supply chains exhibit distinctive characteristics that may amplify the benefits of investing in digital infrastructure. They operate in highly uncertain, resource-constrained, and geographically dispersed environments (Van Wassenhove, 2006; Altay et al., 2018). They depend on multi-actor coordination across INGOs, UN agencies, national governments, and private sector logistics providers, creating severe information asymmetries that digital infrastructure is well positioned to address (Falagara Sigala & Maghsoudi, 2022). They face demand patterns driven by sudden-onset crises — natural disasters, conflict escalations, disease outbreaks — that are inherently difficult to forecast, amplifying the value of real-time IoT sensing and AI-assisted demand capabilities (Dubey et al., 2019).

A recent bibliometric analysis of 4,780 Scopus-indexed documents on digital technology and humanitarian supply chains (2015–2025) identified digitalisation as an expanding technology-led field with four dominant research clusters: AI-driven forecasting, logistics optimisation, last-mile operations, and data analytics platforms (Kruger & Schutte, 2026; identified post-search cutoff, included as supplementary context only). However, despite this volume of literature, the vast majority of existing studies in this space are qualitative, conceptual, or bibliometric. Quantitative empirical studies reporting standardised effect sizes on the digital infrastructure-SCR relationship in NPIO contexts are extremely scarce, rendering meta-analytic synthesis premature at this stage.

This scarcity reflects genuine barriers: NPIOs frequently lack standardised performance measurement systems, limiting the production of quantifiable supply chain data (De Boeck et al., 2023; Prasad et al., 2018). Power imbalances between donor organisations and implementing partners create incentive misalignments, impeding information sharing. Digital infrastructure in low-resource humanitarian settings is constrained by connectivity gaps, limited technical capacity, and the absence of interoperable systems across agencies (Altay et al., 2018; Falagara

Sigala & Maghsoudi, 2022). Despite these barriers, emerging empirical signals are positive: Singh (2025) demonstrates that digital twin technology can transform resilience and agility in humanitarian supply chains, and quantitative studies of AI-BDA in NGOs across Ghana and South Africa report significantly enhanced resilience outcomes (Mohamad et al., 2025).

This study, therefore, calls on the research community to accelerate primary quantitative research on digital infrastructure and SCR in NPIO contexts. Specifically, future research should prioritise: (1) longitudinal empirical designs capturing the dynamic, phase-dependent nature of humanitarian supply chain operations; (2) standardised measurement of digital infrastructure and SCR constructs enabling cross-study comparability; (3) multi-level designs capturing both organisational-level and network-level resilience outcomes; and (4) attention to context-specific moderators, including host-country infrastructure, donor policy frameworks, and inter-agency coordination quality. As the primary literature in this domain matures, a future meta-analysis will provide the cumulative evidence base needed to guide digital investment decisions in one of the world's most operationally challenging supply chain environments.

### *5.5 Theoretical Contributions*

This study makes three theoretical contributions. First, it extends dynamic capabilities theory by providing meta-analytic evidence that digital infrastructure — as a foundational, multi-dimensional capability layer — consistently enables higher-order SCR capabilities. This moves beyond the common DCT application of examining individual technologies and instead treats infrastructure as an integrative organisational asset whose value derives from the interoperability and complementarity of its component systems. Second, it extends RBV by empirically demonstrating the diminishing returns prediction at a sector level: manufacturing's directionally larger effect vis-à-vis service sectors is consistent with the expectation that resource value is greatest when capability gaps are largest. Third, it introduces the NPIO sector as a theoretically significant and empirically underexplored context where existing theory may require modification — particularly regarding how resource constraints, multi-actor governance, and crisis-driven operating conditions reshape the digital-resilience relationship.

## 6. Practical Implications

For supply chain managers in the manufacturing sector, the findings provide strong empirical support ($r = 0.48$) for digital infrastructure investment as a strategic resilience lever. Organisations at early or intermediate stages of digital maturity stand to gain the most from investments in cloud-based supply chain platforms, ERP-IoT integration, and cross-tier supplier visibility systems. Prioritising breadth of digital connectivity — bringing previously offline supply network nodes into the digital ecosystem — is likely to yield the largest near-term resilience gains.

For service-sector organisations, the findings caution against complacency regarding digital maturity. Despite a smaller pooled effect ($r = 0.44$), the relationship remains strongly positive, suggesting that targeted investment in resilience-specific digital capabilities — multi-cloud redundancy, AI-driven risk monitoring, and cyber-resilient network architectures — continues to deliver meaningful supply chain benefits. The negligible heterogeneity within the service-sector subgroup ($Q(4) = 1.32$, $p = .858$, $I^2 = 0.0\%$) also suggests that the findings generalise well across diverse service contexts, including healthcare, logistics, and cross-sector organisations.

For policymakers and international development actors, the NPIO frontier identified in this study has immediate practical relevance. International bodies such as OCHA, WFP, and major INGOs, including Oxfam and MSF, should treat digital infrastructure investment as a core supply chain resilience strategy rather than a secondary administrative concern. Policy frameworks should address the structural barriers — connectivity gaps, interoperability failures, and the absence of standardised performance measurement systems — that currently prevent humanitarian organisations from capturing the digital-resilience benefits documented in commercial sectors.

## 7. Limitations

This study is subject to several limitations that should inform the interpretation of the findings and future research directions. First, the meta-analysis is restricted to English-language publications indexed in Scopus and Web of Science, which may introduce publication and linguistic bias despite supplementary Google Scholar searches. Second, the geographic concentration of the sample is a notable limitation: 12 of 15 studies originate from Asia-Pacific contexts (seven from China), and only three from European or Western settings. This constrains the generalisability of regional comparisons. Third, the sector classification of manufacturing versus service organisations involves some degree of discretionary boundary judgment; the criteria applied are documented but remain subject to researcher judgment. Fourth, converting diverse effect size statistics (regression coefficients, path coefficients) to Pearson's r involves approximation, and effect sizes are subject to conversion error; established correction procedures (Hunter & Schmidt, 2004; Borenstein et al., 2009) were applied throughout to minimise this error. Fifth, the 15-study sample, while sufficient for a meta-analysis and consistent with comparable meta-analyses in the supply chain and operations management literature (e.g., Ataseven & Nair, 2017, k = 16; Liao et al., 2025, k = 18), limits the statistical power of subgroup and moderator analyses; in particular, the non-significant between-sector difference (p = .124) may reflect the limited number of studies rather than a true boundary effect. Sixth, data extraction was conducted by a single coder with self-consistency checks rather than independent dual coding; the absence of independent double extraction is a limitation relative to best-practice meta-analytic standards. Seventh, the cross-sectional nature of most primary studies precludes causal inference; the meta-analytic pooled effect reflects association rather than verified causal impact. Eighth, the service-sector subgroup comprised only k = 5 studies, well below the $k \geq 8$ threshold commonly recommended for reliable subgroup estimates (Borenstein et al., 2009), thereby limiting the statistical power of the sector comparison and warranting caution in interpreting the directional difference between manufacturing and service contexts. Ninth, two included studies — Lin & Fan (2024) and Jing & Fan (2024) — share a common second author, and both employ Chinese panel data with the same analytical method; while the two papers draw on distinct datasets and research questions, potential sample overlap between their underlying firm panels cannot be independently verified from the published articles. Readers should note this as a caveat to the assumed independence of these two effect size estimates within the meta-analytic model.

## 8. Conclusion

This meta-analysis synthesised 15 empirical studies (N = 4,186). It confirmed that digital infrastructure investment is a robust, medium (approaching the large-effect threshold) predictor of supply chain resilience (r = 0.47), with moderate heterogeneity across diverse contexts. Manufacturing-sector organisations exhibited a directionally stronger relationship (r = 0.48) than service-sector organisations (r = .44), a finding consistent with resource-based diminishing returns predictions, though the between-sector difference did not reach conventional statistical significance (p = 0.124). The sector comparison (manufacturing r = .48 vs service r = 0.44) should be interpreted with caution: the service-sector subgroup comprised only k = 5 studies, well below the $k \geq 8$ threshold commonly recommended for reliable subgroup estimates, limiting statistical power for this comparison. Moderator analyses identified digital maturity (as a convergent extension of the sector comparison) as a directional boundary condition, with firm size producing a theoretically consistent but non-significant exploratory trend. Geographically, 80% of included studies originate from Asia-Pacific contexts; generalisability to European, North American, and sub-Saharan African contexts remains an open empirical question requiring dedicated primary research. Leave-one-out sensitivity analyses confirmed that the pooled estimate is highly stable across all study permutations. Publication bias assessment via Egger's test (p = 0.726) and a fail-safe N of 5,709 provided strong evidence that bias does not explain the findings.

Critically, this study identifies not-for-profit international organisations as a theoretically urgent but empirically underdeveloped sector in the digital-resilience literature. The theoretical case for digital infrastructure as an SCR enabler in humanitarian supply chains is compelling, yet quantitative primary studies remain too few for meta-analytic synthesis. Building the empirical foundation for this future synthesis — through rigorous primary quantitative studies in INGO and UN agency contexts — is a research agenda of priority with direct implications for some of the world's most complex and consequential supply chain environments.

## Author Contributions

**Samuel O. Fakunle:** Conceptualisation, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualisation, Project administration.

**Bright Onyedikachi Asonye:** Methodology, Visualisation, Project administration, Supervision.

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## Data Availability Statement

All data used in this study are derived from published primary sources cited in the reference list. No new data were created or analysed in this study. Data sharing is not applicable.

## Conflicts of Interest

The authors declare no conflicts of interest.

## Ethics Statement

This study is a secondary meta-analysis based exclusively on published, publicly available data. No primary data collection was conducted, and no human participants, personal data, or animal subjects were involved. Accordingly, ethical review and informed consent were not required.

### Appendix A: Full Boolean Search String

The following Boolean search string was applied to title, abstract, and keyword fields in Scopus and Web of Science on 15 February 2024, with a supplementary update search on 20 December 2024:

> TITLE-ABS-KEY ( ( "digital infrastructure" OR "digital transformation" OR "IT infrastructure" OR "information technology capability" OR "enterprise systems" OR "ERP" OR "cloud computing" OR "IoT" OR "Internet of Things" OR "big data analytics" OR "Industry 4.0" OR "digital supply chain" ) AND ( "supply chain resilience" OR "supply chain robustness" OR "supply chain agility" OR "SC resilience" OR "resilient supply chain" ) ) AND PUBYEAR > 2018 AND ( LIMIT-TO ( DOCTYPE , "ar" ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) )

The same logical structure was adapted for Web of Science field codes (TS= for topic, PY= for publication year, DT=Article for document type). A supplementary Google Scholar search was conducted using the terms “digital infrastructure supply chain resilience meta-analysis” and “digital transformation supply chain resilience empirical” to identify grey literature and potentially missed studies.

### Appendix B: Coding Template (Key Variables Extracted)

The following variables were coded for each study during data extraction:

1. Bibliographic: Author(s), publication year, journal name, volume, pages, DOI
2. Study context: Country, sector classification, organisational type, time period
3. Sample: Total sample size (n), sampling method, response rate (if survey)
4. Constructs: Digital infrastructure operationalisation (construct name, measurement items, scale source), SCR operationalisation (construct name, measurement items, scale source, dimensions included)
5. Methods: Analytical approach, software used, model fit indices reported
6. Effect size: Reported statistic (r, β, path coefficient, regression coefficient), degrees of freedom, converted Pearson r, Fisher z transformation, sampling variance
7. Quality: Sample adequacy (≥ 100), reliability (α or CR ≥ .70), CMB controls applied
8. Moderators: Digital maturity classification, firm size classification, geographic region

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