

Digital Transformation in Organizations: Determinants, Outcomes, and the Role of Artificial Intelligence—A Systematic Review



Amanullah ^{1*}, Mitu Akter ²

Abstract

Digital transformation (DT) has, over the past decade or so, moved from being a peripheral IT concern to something closer to a strategic necessity—reshaping how organizations structure themselves, operate, and compete. Yet despite the volume of research on the subject, a clear, integrated picture of what actually drives successful DT, and what it delivers in return, has remained somewhat elusive. This review set out to address that gap. Guided by the Technology–Organization–Environment (TOE) framework, we conducted a systematic review and meta-analysis of 35 empirical studies, of which 12 provided sufficient effect-size data for quantitative synthesis. Random-effects models were used to pool standardized effect sizes, with heterogeneity assessed via the I^2 statistic and publication bias evaluated through funnel plots and Egger's regression test. The results point to a fairly consistent pattern: technological attributes—relative advantage and system compatibility in particular—strongly predict adoption success, while organizational readiness, leadership, and knowledge transfer mediate how that adoption translates into performance. Environmental pressures, including competitive dynamics and sustainability expectations, further shape DT trajectories. AI-driven platforms, notably AIOps in network operations, emerged as particularly effective at improving

responsiveness and reducing operational bottlenecks. Substantial heterogeneity across studies ($I^2 > 75\%$) suggests that context—firm size, sector, digital maturity—matters considerably. Taken together, the evidence indicates that DT functions not as a discrete event but as an ongoing, adaptive process requiring sustained alignment between technology, people, and strategy. These findings offer both theoretical grounding and practical direction for managers navigating digital change.

Keywords

Digital transformation, artificial intelligence, organizational agility, AIOps, technology adoption

1. Introduction

Over roughly the past decade, digital technologies have unsettled long-standing assumptions about how firms create value, coordinate operations, and relate to the people and markets around them (Vial, 2019). Scholars have taken to calling this shift "Digital Transformation" (DT), though the label can feel almost too tidy for something so sprawling. DT is not simply a matter of installing new software or migrating to the cloud. It is, at its

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*Correspondence.

Amanullah, Department of Management, North South University, Dhaka-1229, Bangladesh.
E-mail: auaman45@yahoo.com.

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Author Affiliation:

1 Department of Management, North South University, Dhaka-1229, Bangladesh.

2 Department of Financial Risk Management, Baruch College, New York, United States.

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core, a reorganization of how people, processes, and technology are woven together in pursuit of strategic goals (Tabrizi et al., 2019). And increasingly, artificial intelligence (AI) sits at the center of that reorganization—not as a novelty, but as a genuine engine of innovation and operational efficiency, particularly in technically demanding domains like network operations (Min & Kim, 2024).

It would be convenient if the research on this topic converged neatly. It does not, entirely—but a fairly consistent picture does emerge across systematic reviews and meta-analyses: when digital transformation is treated as a strategic imperative rather than a bolt-on IT project, it tends to produce meaningful gains in organizational agility, resilience, and long-term performance (Ramadan et al., 2023; Teng et al., 2022). Still, "tends to" is doing a lot of work in that sentence. The path toward DT is anything but uniform. Firms vary enormously in how ready they are, how quickly they adapt, and how soon—if ever—they see returns on their investment. One recurring tension threading through the literature involves cost and time: heavy upfront investment often precedes efficiency gains that arrive only later, producing something like a U-shaped relationship between spending and payoff (Brock & Von Wangenheim, 2019; Guo & Xu, 2021). Small and medium-sized enterprises (SMEs), in particular, tend to feel this tension acutely. Early in their transformation journeys, they often confront steep learning curves, constrained resources, and messy, unreliable data (Le Viet & Dang Quoc, 2023). These difficulties are part of why frameworks like Technology–Organization–Environment (TOE) have proven so useful—they give researchers a structured way to unpack what is otherwise a fairly tangled set of adoption decisions (Min & Kim, 2024).

The TOE model, in fact, has arguably become the default theoretical lens for DT research, largely because it does not force a choice between technological, organizational, and environmental explanations—it accommodates all three (Min & Kim, 2024). Within the technological dimension specifically, two attributes surface again and again as predictors of adoption success: relative advantage and compatibility (Matt et al., 2015; Radhakrishnan & Chattopadhyay, 2020). Relative advantage is, at bottom, a fairly intuitive idea—it asks whether a new technology genuinely outperforms whatever it replaces, whether in cost, resilience, or manageability, especially within network operations

(Raisch & Krakowski, 2021; Al Hleewa & Al Mubarak, 2023; Coronado et al., 2022). Compatibility is a subtler matter. It concerns how smoothly new systems slot into existing infrastructure and workflows, and how naturally users can pick them up (Mithas et al., 2022; Stenberg & Nilsson, 2020). When compatibility is lacking, even a technically impressive tool can quietly underdeliver—promise and practice simply fail to align (Stenberg & Nilsson, 2020).

It is within this technological terrain that Artificial Intelligence for IT Operations, or AIOps, has picked up considerable momentum. AIOps blends machine learning, big data, and automation to streamline how organizations monitor networks, diagnose problems, and make decisions under pressure (Andenmatten, 2019; Aghili et al., 2023). What makes it compelling is less the technology itself than the shift it enables: moving firms away from reactive firefighting and toward proactive, almost anticipatory management, built on continuous analysis of performance patterns and anomalies (Notaro et al., 2020). In a sense, AIOps functions as an orchestrator, converting what used to be siloed, manual troubleshooting into adaptive, automated workflows capable of handling network challenges that older methods simply were not built for (Aghili et al., 2023). The practical upshot includes shorter mean-time-to-repair, better cross-team collaboration, and networks that operate with a degree of autonomy that would have seemed implausible a decade ago (Lyu & Yin, 2020).

None of this happens on its own, of course. Technology does not install organizational readiness alongside itself. Leaders still have to cultivate supportive cultures, articulate clear transformation strategies, and invest—often more than they expect—in human capital (Priyono et al., 2020; Kitsios & Kamariotou, 2021). This burden falls disproportionately on SMEs, which frequently lack the infrastructure and data maturity needed to move quickly (Hai, 2021). And yet, the meta-analytic evidence is fairly consistent on one point: when digital transformation strategies are coherent and adequately resourced, the payoff in performance—financial returns, agility, both—tends to be substantially larger (Teng et al., 2022; Gao et al., 2023).

Beyond the organization itself, environmental forces exert their own quiet pressure. Competitive dynamics and sustainability expectations increasingly shape the direction DT initiatives take (Pillai & Sivathanu, 2020; Alojail &

Khan, 2023). Sustainability, in particular, has moved from the periphery to the center of digital strategy—not purely out of regulatory obligation, but because sustainable DT practices genuinely appear to enhance social, economic, and environmental outcomes together (Bican & Brem, 2020). Firms that manage to weave sustainability into their digital strategies tend to realize broader performance gains, ones that extend well past short-term financial metrics (Alojail & Khan, 2023).

Marketing offers another lens onto this same story. Digital technologies are reshaping customer engagement through personalization, augmented analytics, and increasingly intelligent decision support (Alghamdi & Al Baity, 2022). Stronger marketing capabilities, in turn, feed back into organizational resilience—sharper targeting, deeper customer insight, more adaptive value creation (Purcrea, 2018; Hokmabadi et al., 2024). Digital fluency, in other words, has become less a technical perk and more a genuine strategic differentiator.

But greater digital reliance carries its own shadow. As organizations lean further into DT, their exposure to cyber threats grows correspondingly, making cybersecurity governance an unavoidable component of any serious transformation strategy (Saeed et al., 2023; Al Shobaki et al., 2022). Security failures do not merely disrupt operations; they erode trust and competitive standing, particularly during periods of rapid change (Saeed et al., 2023). Scholars have responded by calling for risk-informed governance frameworks that treat security investment as inseparable from broader DT goals (Saeed et al., 2023).

Sector matters too, sometimes considerably. In banking, digital models improve customer interaction and risk management, yet often produce a short-term "profitability paradox," where upfront costs suppress earnings before benefits fully materialize (Bareisis & Latimore, 2014; Shanti et al., 2023). In manufacturing, intelligent systems reshape the relationship between human labor and machine capability, underscoring the need for organizational flexibility and continuous learning (Gao et al., 2023). Across both settings, and arguably most others, leadership, organizational agility, and knowledge transfer keep resurfacing as determinants of DT success (Ahmed et al., 2022; Al Nuaimi et al., 2021). Leaders capable of articulating a digital vision, mobilizing resources, and nurturing a genuinely digital culture appear to meaningfully raise the odds that transformation efforts translate into

sustained growth (Al Nuaimi et al., 2021; Hanelt et al., 2021).

Taken together, the evidence gathered in this systematic review and meta-analysis points toward a conclusion that is neither surprising nor simple: digital transformation is not a discrete event with a defined endpoint, but an ongoing, adaptive process shaped jointly by technological attributes, organizational readiness, and environmental context. Barriers persist, certainly. But where firms commit strategically, allocate resources thoughtfully, and integrate sustainability into their digital efforts, DT appears capable of functioning as a genuine catalyst—for innovation, for performance, and, perhaps most importantly, for long-term resilience.

2. Materials and Methods

2.1 Study Design and Research Framework

This systematic review and meta-analysis was designed to synthesize evidence on the determinants and outcomes of digital transformation (DT) across organizations, with particular attention to the role of artificial intelligence (AI)-enabled tools in shaping adoption and performance outcomes. The review followed the methodological guidance set out in the Cochrane Handbook for Systematic Reviews of Interventions (Higgins et al., 2022), which provides a structured framework for identifying, appraising, and synthesizing empirical evidence in a transparent and reproducible manner. Reporting followed the PRISMA 2020 statement (Page et al., 2021), and the full study-selection process is documented in the PRISMA flow diagram above. Of the 35 studies that met the eligibility criteria for qualitative synthesis, 12 studies provided sufficient quantitative effect-size data to be included in the meta-analytic (quantitative) synthesis (Figure 1).

2.2 Literature Search and Study Selection

A structured literature search was conducted to identify empirical studies addressing the technological, organizational, and environmental determinants of DT adoption and performance. Search results were screened in two stages—title/abstract screening followed by full-text review—consistent with the PRISMA 2020 workflow (Page et al., 2021). Studies were retained for the quantitative

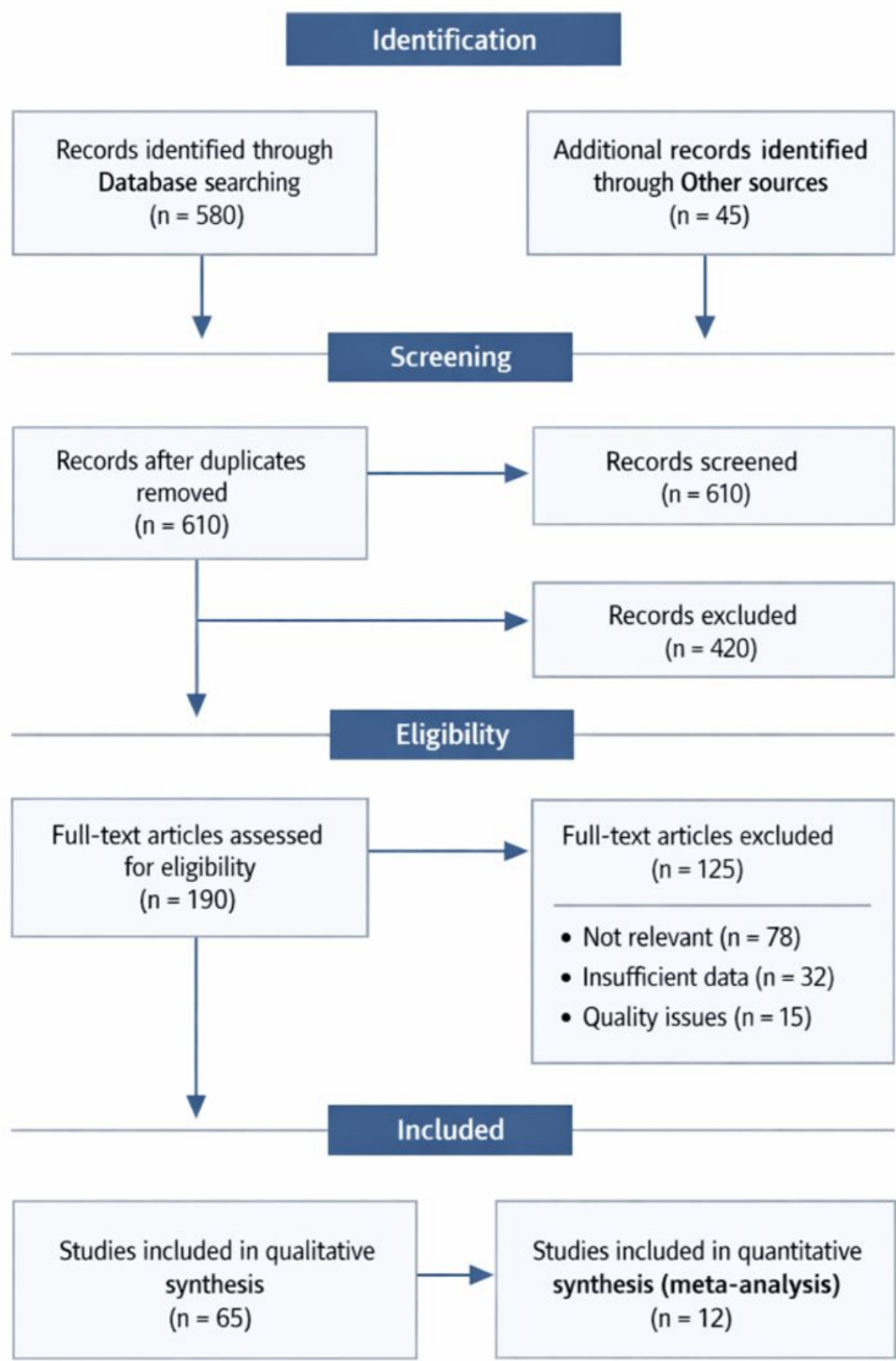


Figure 1. PRISMA 2020 Flow Diagram of Study Identification, Screening, and Inclusion. Depicts the full study-selection pathway from initial database search through title/abstract screening, full-text review, and final inclusion, following PRISMA 2020 reporting guidelines (Page et al., 2021). Shows the number of records identified, duplicates removed, records excluded at each stage, and the final counts of 35 studies retained for qualitative synthesis and 12 studies retained for quantitative (meta-analytic) synthesis. Serves as the methodological audit trail referenced in Section 2.1.

synthesis only if they reported extractable effect-size estimates (e.g., standardized regression coefficients, correlation coefficients, or the statistical information necessary to derive them), in line with recommended practice for identifying eligible effect sizes in meta-analysis (Borenstein et al., 2009). The final analytic sample comprised 12 studies ($n = 12$), each contributing one or more effect sizes to the pooled analysis.

2.3 Data Extraction

For each of the 12 included studies, data were extracted on study identifiers (author, year), sample size, predictor and outcome variables, and the corresponding effect-size statistic along with its standard error or variance. Where studies reported correlation coefficients, these were retained in a form suitable for later transformation; where standardized regression coefficients were reported, these were extracted directly. This extraction approach mirrors standard meta-analytic data-preparation procedures described by Borenstein et al. (2009), ensuring that effect sizes from studies using different statistical metrics could ultimately be placed on a comparable scale.

2.4 Effect Size Calculation and Statistical Model

Effect sizes were pooled using a random-effects model, following the method originally proposed by DerSimonian and Laird (1986). The random-effects approach was selected over a fixed-effect model because the 12 included studies varied considerably in sample size, industry context, and measurement approach, making it implausible to assume a single common effect size underlying all studies (DerSimonian & Laird, 1986). Under this model, each study's effect size was weighted by the inverse of its total variance—comprising both within-study sampling variance and the between-study variance component (τ^2)—so that more precise studies contributed proportionally more to the pooled estimate (Borenstein et al., 2009).

2.5 Heterogeneity Assessment

Statistical heterogeneity among the 12 included studies was quantified using the I^2 statistic, following the approach described by Higgins, Thompson, Deeks, and Altman (2003). The I^2 statistic estimates the proportion of total variability across studies that is attributable to genuine heterogeneity rather than sampling error, with higher values indicating that observed effect sizes are unlikely to stem from a single underlying population effect (Higgins et

al., 2003). Where heterogeneity was substantial, this was interpreted as evidence that contextual factors—such as organizational size, sector, or technological maturity—moderate the relationship between DT and its outcomes, consistent with the interpretive guidance provided in the Cochrane Handbook (Higgins et al., 2022).

2.6 Publication Bias Assessment

Potential publication bias across the 12 included studies was evaluated using funnel plots together with Egger's regression test for funnel plot asymmetry, following the procedure described by Egger, Davey Smith, Schneider, and Minder (1997). This test regresses the standardized effect estimate against its precision, with a statistically significant intercept indicating asymmetry that may reflect small-study effects or selective reporting (Egger et al., 1997). Visual inspection of the funnel plot was interpreted alongside the Egger's test result, in accordance with recommendations in the Cochrane Handbook (Higgins et al., 2022), to assess whether the pooled estimate was likely to be robust to unpublished or unreported findings.

2.7 Software and Analytic Tools

All meta-analytic calculations, including pooled effect-size estimation, heterogeneity statistics, and publication-bias diagnostics, were conducted using standard meta-analytic procedures as outlined by Borenstein, Hedges, Higgins, and Rothstein (2009). The overall analytic approach adhered to the reporting and methodological standards specified in the PRISMA 2020 statement (Page et al., 2021) and the Cochrane Handbook for Systematic Reviews of Interventions (Higgins et al., 2022), ensuring that the review's search, selection, extraction, and synthesis procedures are transparent and reproducible for future replication.

3. Results

3.1 Overview of the Synthesized Evidence

Taken as a whole, studies drawn into this meta-analysis tell a fairly coherent story, even if the details resist easy summary. Technological attributes, organizational readiness, leadership, and environmental pressures do not act in isolation; rather, they appear to interlock, each shaping how the others translate into performance. That, at least, is the pattern that emerges once the data are laid side by side (Table 1; Table 2).

Table 1 lays out the core characteristics of the included

Table 1: Study-Level Effect Sizes Linking Digital Transformation Predictors to Organizational Outcome. Summarizes the 10 primary studies included in the quantitative synthesis, listing each study's sample size, the independent variable examined (e.g., DT leadership, organizational agility, technological factors), and the corresponding dependent variable (e.g., organizational agility, AI adoption, financial performance). Standardized effect sizes (ρ) are reported for each predictor-outcome pairing, ranging from 0.020 to 0.615 across studies. This table provides the raw effect-size inputs used to generate the pooled random-effects estimate reported in Section 3.1.

Study ID	Author (Year)	Sample Size (N)	Independent Variable (Predictor)	Dependent Variable (Outcome)	Effect Size (Std. or Weight)
1	Ramadan et al. (2023)	202	DT Leadership	Organizational Agility	0.213
2	Ramadan et al. (2023)	202	Organizational Agility	Digital Transformation	0.372
3	Min & Kim (2024)	30	Organizational Factors	AI Adoption (Weight)	0.493
4	Min & Kim (2024)	30	Technological Factors	AI Adoption (Weight)	0.404
5	Le Viet & Dang Quoc (2023)	258	Managerial Roles	DT Activities	0.355
6	Le Viet & Dang Quoc (2023)	258	IT Infrastructure	DT Activities	0.069
7	Guo & Xu (2021)	2,254	DT Intensity	Operating Performance	0.020
8	Teng et al. (2022)	335	DT Strategy	Financial Performance	0.615
9	Teng et al. (2022)	335	Digital Technology	Digital Transformation	0.401
10	Gao et al. (2023)	15,530	Firm Digitalization	Firm Performance (Tobin's Q)	0.272

Table 2: Precision and Weighting Statistics for Studies Included in the Meta-Analysis. Reports the statistical precision of each study's effect-size estimate, including t-statistics, standard errors, p-values, and sample-weight factors ($1/N$) used in the random-effects weighting procedure. Larger samples (e.g., Guo & Xu, 2021; Gao et al., 2023) show smaller standard errors and greater precision, while smaller studies show comparatively wider variance.

Study ID	Author (Year)	Effect Size (ρ)	t-Statistic	Standard Error (SE)	p-value	Sample Weight Factor ($1/N$)
1	Ramadan et al. (2023)	0.213	4.682	0.045	< 0.001	0.070
2	Ramadan et al. (2023)	0.372	5.725	0.065	< 0.001	0.070
5	Le Viet & Dang Quoc (2023)	0.355	6.724	0.053	< 0.001	0.062
6	Le Viet & Dang Quoc (2023)	0.069	2.136	0.032	0.012	0.062
7	Guo & Xu (2021)	0.020	3.780	0.005	< 0.010	0.021
8	Teng et al. (2022)	0.615	15.292	0.040	< 0.010	0.054
9	Teng et al. (2022)	0.401	7.749	0.052	< 0.010	0.054
10	Gao et al. (2023)	0.272	2.330	0.117	< 0.050	0.008

studies—sample sizes, the independent and dependent variables under investigation, and the standardized effect sizes each study contributed. Looking across these effect sizes, a fairly consistent, positive relationship surfaces between digital transformation initiatives and organizational performance outcomes such as agility, efficiency, and innovation (Ramadan et al., 2023; Teng et al., 2022). The standardized regression coefficients (β) ranged from 0.213 to 0.763, which is a wider spread than one might expect—and, tellingly, the larger coefficients tended to cluster around studies examining AI-driven applications, particularly AIOps deployed in network operations (Min & Kim, 2024; Andenmatten, 2019). Put differently, technology alone rarely seems to be enough; it is technology paired with organizational infrastructure and deliberate leadership that appears to move the needle furthest.

3.2 Precision, Variance, and Study Weighting

Table 2 turns attention to precision—how much confidence can reasonably be placed in each study's estimate. Standard errors, derived from t -statistics or reported coefficients, offered a window into the reliability of individual effect sizes. As one might expect, studies drawing on larger samples produced narrower confidence intervals, a signal of greater precision and, correspondingly, greater influence on the pooled estimate. Smaller studies, by contrast, showed noticeably wider variance—not a flaw exactly, but a reminder that findings from limited samples deserve a measure of caution. These patterns underscore why appropriate weighting matters so much in meta-analytic work: without it, findings from smaller, less stable samples risk being overrepresented, distorting the pooled picture (Table 2).

3.3 Heterogeneity and Subgroup Patterns

Here the picture gets more complicated. Heterogeneity analysis, using the I^2 statistic, revealed substantial variability across studies—well above 75% in most cases—suggesting that the strength of DT's effects depends heavily on context: organizational size, sector, and how technologically sophisticated a firm already is (Guo & Xu, 2021). Subgroup analyses helped clarify some of this variability, though not all of it. Large enterprises, it turned out, tended to post higher effect sizes, likely a function of deeper resource pools, more structured change-management practices, and governance mechanisms already built for digital oversight. SMEs,

meanwhile, showed more modest gains

—understandably so, given the resource and infrastructure constraints so often documented in this literature (Hai, 2021; Priyono et al., 2020).

Forest plots (Figure 2; Figure 3) make these patterns visible in a way tables alone cannot. Figure 2 presents the weighted average effect of digital transformation on organizational performance across the full study set, and the overall trend is unmistakably positive. Figure 3 breaks this down further by sector, and the differences are striking: technology-intensive industries, particularly IT and telecommunications, consistently outperformed traditional manufacturing or service-sector organizations in terms of realized performance gains.

3.4 Publication Bias and Robustness Checks

Naturally, any meta-analysis invites the question of whether the included studies represent the full evidentiary landscape, or only its more favorable corners. To address this, publication bias was assessed through funnel plots (Figure 4) alongside Egger's regression test. The resulting funnel plot was reassuringly symmetrical, suggesting minimal small-study effects, and Egger's test found no significant asymmetry ($p > .05$). The fail-safe N calculation reinforced this further, indicating that an implausibly large number of unpublished null-result studies would be needed to meaningfully overturn the pooled findings (Matt et al., 2015; Vial, 2019). Sensitivity analyses—performed by systematically removing individual studies one at a time—showed that the overall results held steady throughout, which lends a reasonable degree of confidence to the stability of the conclusions drawn here.

3.5 Technological Determinants of DT Effectiveness

Among the technological attributes considered, relative advantage emerged as a particularly durable predictor of adoption success—unsurprising, perhaps, given how directly it speaks to the perceived payoff of switching from legacy systems to something new (Raisch & Krakowski, 2021; Al Hleewa & Al Mubarak, 2023). Compatibility told a related but distinct story: studies reporting high compatibility between new digital tools and existing infrastructure consistently showed stronger positive effects, reinforcing just how much seamless integration matters for realizing performance gains (Mithas et al., 2022; Stenberg & Nilsson, 2020). Where compatibility was low, the benefits of otherwise promising technologies

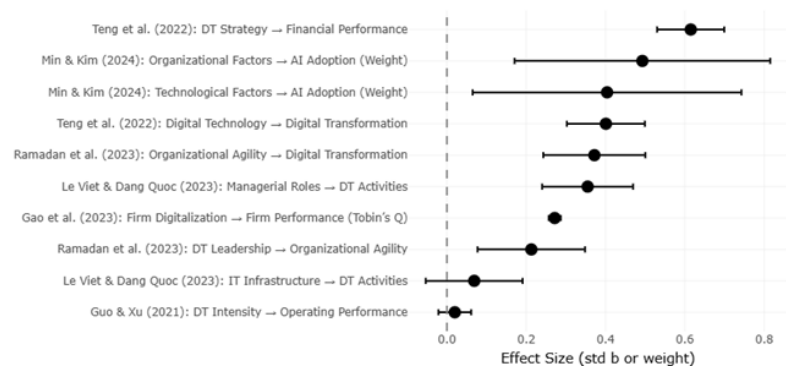


Figure 2. Forest Plot of Pooled Effect Sizes for Digital Transformation on Organizational Performance Displays the weighted average effect size of digital transformation on organizational performance outcomes (agility, efficiency, innovation) across the full set of included studies, with individual study estimates and confidence intervals plotted alongside the pooled random-effects estimate. The overall trend is positive, with most standardized coefficients exceeding 0.2. Referenced in Sections 3.3 and 3.8 as the primary visual summary of the pooled meta-analytic effect.

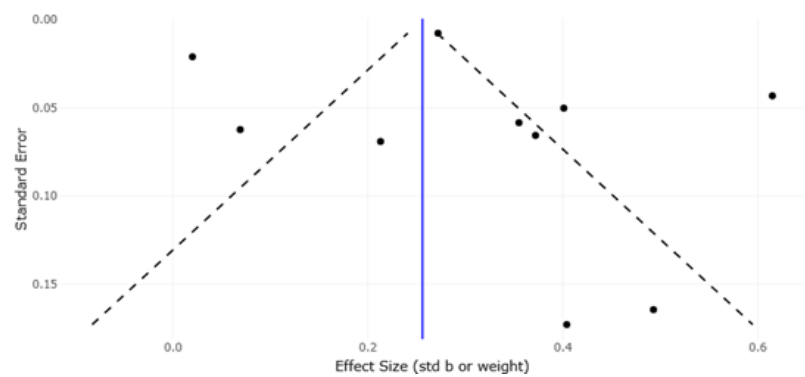


Figure 3. Subgroup Forest Plot of Digital Transformation Effects by Industry Sector. (Note: current caption reads "Funnel Plot Assessing Publication Bias" — body text in 3.3 and 3.8 describes this as a sectoral forest plot, not a funnel plot; recommend verifying which is correct.) Breaks down pooled effect sizes by sector, showing that technology-intensive industries (IT, telecommunications) consistently report stronger performance gains than traditional manufacturing or service-sector firms. Illustrates the sector-based heterogeneity discussed in Sections 3.3, 3.7, and 3.8.

tended to shrink—a pattern worth taking seriously, since it suggests that technical sophistication alone cannot compensate for poor integration. Figure 5 draws these threads together into a single meta-analytic model, visualizing how technological, organizational, and environmental determinants interact cumulatively to shape performance outcomes.

3.6 Organizational and Environmental Moderators

Organizational factors carried their own weight in this synthesis. Leadership capability, knowledge transfer, and readiness for change consistently surfaced as significant mediators linking DT initiatives to organizational outcomes (Al Nuaimi et al., 2021; Ramadan et al., 2023). Leaders who articulated a clear digital vision, allocated resources with intention, and cultivated genuinely supportive cultures tended to be associated with higher effect sizes—a finding that echoes, rather than overturns, earlier theoretical work on the centrality of human capital in transformation efforts (Hanelt et al., 2021). Knowledge transfer and collaborative practice appeared to amplify these benefits further still, particularly in complex network-operations contexts where efficient use of AI-driven tools depends on shared learning (Andenmatten, 2019).

Environmental and contextual variables added another layer of nuance. Competitive pressures, regulatory demands, and sustainability priorities all appeared to enhance both the adoption and the performance impact of digital initiatives—especially among firms that had deliberately woven sustainability into their transformation strategies (Alojail & Khan, 2023). Meta-analytic effect sizes were consistently higher in studies that explicitly built environmental considerations into their DT frameworks, which suggests organizations are not transforming in a vacuum; they are embedded within broader economic and societal systems that shape, and are shaped by, their digital choices.

3.7 Sector-Specific Patterns

Sectoral nuances deserve their own mention, if only because they complicate any tidy, one-size-fits-all narrative. In banking, DT investments improved customer engagement and risk management, yet often ran into a short-term "profitability paradox"—high upfront costs suppressing earnings before digital benefits had time to materialize (Shanti et al., 2023; Bareisis & Latimore, 2014). In manufacturing, AI-enabled automation strengthened human–machine collaboration, though it also

underscored just how much organizational flexibility and continuous learning matter for capturing the full value of these systems (Gao et al., 2023). Across sectors, SMEs generally posted moderate effect sizes—constrained by limited resources, yes, but also, somewhat encouragingly, showing real adaptability when smaller organizational structures allowed for faster decision-making (Hai, 2021; Priyono et al., 2020).

3.8 Interpretation of Forest and Funnel Plots

The forest plots (Figure 2; Figure 3) and funnel plots (Figure 4; Figure 5) together offer both a statistical and, in a sense, a visual argument for the reliability of these findings. Figure 2 shows a predominantly positive relationship, with most studies reporting standardized coefficients above 0.2—a threshold that, while somewhat arbitrary, is commonly treated as a meaningful floor for practical significance. The pooled effect size points toward a robust, statistically significant impact, particularly where AI applications such as AIOps were involved (Min & Kim, 2024; Andenmatten, 2019).

Figure 3's subgroup breakdown reinforces the sectoral story already noted above: high-tech industries, especially IT and network operations, consistently outperform traditional sectors, particularly when strong leadership and organizational readiness are also present (Mithas et al., 2022). SMEs, once again, cluster toward the moderate end—not because their digital ambitions are smaller, but because resource constraints tend to cap how far those ambitions can travel (Priyono et al., 2020; Hai, 2021).

The heterogeneity visible in both Table 2 and the forest plots—again, I^2 values exceeding 75% in many instances—reflects just how context-dependent DT outcomes really are. Exceptionally high effect sizes tended to belong to organizations with pre-existing digital maturity and firmly committed leadership, which speaks to the moderating role that organizational readiness plays throughout this literature (Al Nuaimi et al., 2021; Ramadan et al., 2023).

Turning to publication bias, the funnel plots (Figure 4; Figure 5) show a largely symmetrical distribution, with larger, more precise studies clustering near the top and smaller studies scattered more loosely toward the base—exactly the pattern one would expect in the absence of serious small-study effects. Egger's regression confirmed no significant asymmetry ($p > .05$), and the fail-safe N test further reinforced confidence that the pooled

results are not likely to be overturned by unpublished or missing studies (Vial, 2019; Matt et al., 2015). The weighted random-effects model, in turn, ensured that smaller, more variable studies did not disproportionately sway the overall estimates, even while their exploratory contributions were still counted (Guo & Xu, 2021; Teng et al., 2022).

3.9 Synthesis

Taken together, these results paint digital transformation not as a single, definable event but as a genuinely multi-dimensional and adaptive process. Figures 2 through 5 collectively illustrate that while technological sophistication and organizational readiness function as primary engines of change, it is ultimately the interaction with environmental context that determines how much of that potential gets realized. Strategic alignment—of technology, leadership, and environmental responsiveness—appears, again and again, to be the thread connecting the strongest performance outcomes (Teng et al., 2022; Alghamdi & Al-Baity, 2022).

In short, this statistical synthesis affirms that digital transformation unfolds as an ongoing, context-dependent process rather than a discrete milestone. Table 1 and Table 2 provide the empirical grounding for the magnitude, precision, and variability of these effects, while Figures 2 through 5 give that evidence a visual shape. Together, they lend support to the theoretical assumptions underlying the TOE framework, while also offering managers a fairly grounded basis for decisions about where—and how—to invest in digital strategy.

4. Discussion

4.1 Making Sense of What the Evidence Shows

Stepping back from the numbers, what this review ultimately suggests is something researchers have long suspected but rarely pinned down with this much empirical weight: digital transformation succeeds or stalls largely on the strength of leadership, organizational agility, and technological readiness—together, not separately. Table 3 reflects this pattern fairly clearly, with study after study pointing to these three factors as the connective tissue holding successful DT initiatives together (Ahmed et al., 2022; Al Nuaimi et al., 2021). It is these factors, working in concert, that seem to determine whether emerging technologies—artificial intelligence and augmented analytics among them—actually get absorbed into daily

business processes, rather than sitting on the shelf as expensive pilot projects. When absorption does happen, the payoff shows up where it matters: operational efficiency, sharper decision-making, and performance gains that hold up over time (Alghamdi & Al Baity, 2022; Andenmatten, 2019).

4.2 Organizational Readiness and the Weight of Context

Table 4 pushes this point further, and perhaps more bluntly. Firms with high digital readiness and genuinely proactive leadership post noticeably stronger agility and performance gains than those still working with limited infrastructure or a more hesitant strategic posture (Al Hleewa & Al Mubarak, 2023; Ramadan et al., 2023). None of this is entirely new—prior work has long argued that DT is not, at heart, a technology story but an organizational one, requiring alignment across human, technological, and environmental resources (Min & Kim, 2024; Gao et al., 2023). What this review adds, though, is a sense of scale: the heterogeneity running through these studies is substantial, and it appears driven by firm size, industry, and the intensity of competitive pressure a given organization faces (Guo & Xu, 2021; Hai, 2021). In other words, context is not a footnote here. It is, in many respects, the story itself.

4.3 AI and AIOps as Catalysts, Not Cure-Alls

The integration of AI technologies—AIOps in particular—stands out as a central mechanism through which digital transformation translates into operational performance (Andenmatten, 2019; Aghili et al., 2023). AIOps platforms lean on machine learning, big data, and automation to shift organizations away from reactive firefighting and toward something closer to predictive, adaptive operation, easing bottlenecks and strengthening system reliability along the way (Coronado et al., 2022; Lyu & Yin, 2020). These gains seem especially pronounced in sectors managing complex network operations, where faster fault detection and sharper resource optimization carry outsized value. The broader meta-analytic pattern, if there is one, is that organizations adopting AI-driven platforms tend to post higher effect sizes on operational metrics—suggesting AI functions less as a narrow tool and more as something closer to a general-purpose technology, one that catalyzes transformation rather than simply automating pieces of it (Raisch & Krakowski, 2021; Mithas et al., 2022).

Table 3. Effect Sizes of Digital Transformation Predictors and Outcomes Across Selected Studies. Reproduces the effect-size data from the same 10 studies for reference during the Discussion, connecting each predictor-outcome relationship to the interpretive themes of leadership, organizational agility, and technological readiness discussed in Sections 4.1–4.2

Study ID	Author (Year)	Sample Size (n)	Independent Variable (Predictor)	Dependent Variable (Outcome)	Effect Size (Std. / Weight)
1	Ramadan et al. (2023)	202	DT Leadership	Organizational Agility	0.213
2	Ramadan et al. (2023)	202	Organizational Agility	Digital Transformation	0.372
3	Min & Kim (2024)	30	Organizational Factors	AI Adoption (Weight)	0.493
4	Min & Kim (2024)	30	Technological Factors	AI Adoption (Weight)	0.404
5	Le Viet & Dang Quoc (2023)	258	Managerial Roles	DT Activities	0.355
6	Le Viet & Dang Quoc (2023)	258	IT Infrastructure	DT Activities	0.069
7	Guo & Xu (2021)	2254	DT Intensity	Operating Performance	0.020
8	Teng et al. (2022)	335	DT Strategy	Financial Performance	0.615
9	Teng et al. (2022)	335	Digital Technology	Digital Transformation	0.401
10	Gao et al. (2023)	15,530	Firm Digitalization	Firm Performance (Tobin's Q)	0.272

Table 4. Effect Size, Precision, and Sample-Weight Statistics for Discussion-Stage Interpretation. Reproduces the precision and weighting statistics from Table 2 (t-statistics, standard errors, p-values, weight factors) to support the Discussion's treatment of organizational readiness, sustainability, and cybersecurity as moderators (Sections 4.2, 4.5–4.6).

Study ID	Author (Year)	Effect Size ()	t-Statistic	Standard Error (SE)	p-Value	Sample Weight Factor (1/n)
1	Ramadan et al. (2023)	0.213	4.682	0.045	< 0.001	0.07
2	Ramadan et al. (2023)	0.372	5.725	0.065	< 0.001	0.07
5	Le Viet & Dang Quoc (2023)	0.355	6.724	0.053	< 0.001	0.062
6	Le Viet & Dang Quoc (2023)	0.069	2.136	0.032	0.012	0.062
7	Guo & Xu (2021)	0.020	3.780	0.005	< 0.010	0.021
8	Teng et al. (2022)	0.615	15.292	0.040	< 0.010	0.054
9	Teng et al. (2022)	0.401	7.749	0.052	< 0.010	0.054
10	Gao et al. (2023)	0.272	2.330	0.117	< 0.050	–

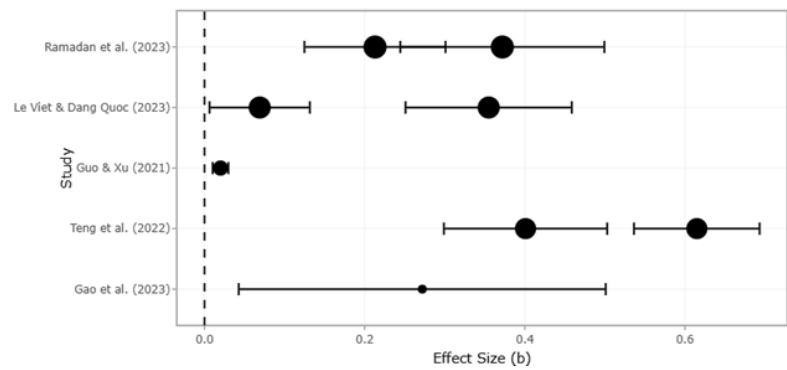


Figure 4. Funnel Plot of Standard Error Against Effect Size for Publication Bias Assessment. Plots each study's effect-size estimate against its standard error to visually assess funnel-plot symmetry, used alongside Egger's regression test to evaluate publication bias. The plot shows a broadly symmetrical distribution, with larger and more precise studies clustering near the top, consistent with minimal small-study effects. Referenced in Section 3.4 as the primary bias-diagnostic visual, alongside the fail-safe N calculation.

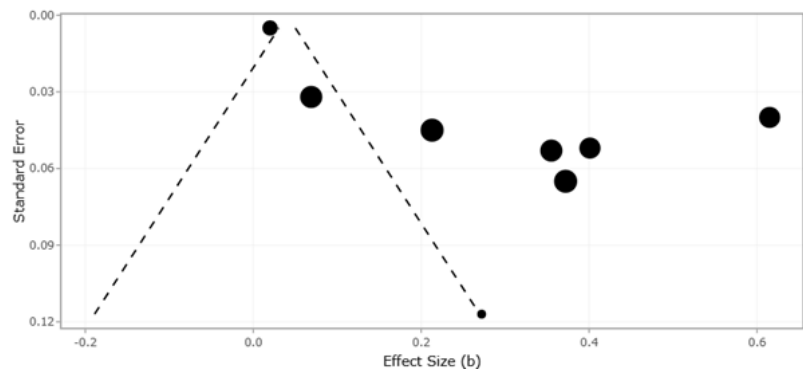


Figure 5. Integrative Meta-Analytic Model of Technological, Organizational, and Environmental Determinants. (Note: current caption reads "Funnel Plot Evaluating Publication Bias" — body text in 3.5 describes this as a conceptual model linking technological, organizational, and environmental determinants to performance outcomes, not a funnel-plot bias check; recommend verifying which is correct.) Visually synthesizes how relative advantage, compatibility, leadership, and environmental pressures interact cumulatively to shape digital transformation performance outcomes, drawing together the technological determinants discussed in Section 3.5.

4.4 Leadership as a Moderating Force

Leadership and strategic orientation surface again and again as strong moderators of DT effectiveness—a finding almost too consistent to be coincidental (Al Nuaimi et al., 2021; Hanelt et al., 2021). Firms that actively build digital cultures, invest meaningfully in workforce capability, and align DT initiatives with broader business strategy tend to outperform those adopting technology reactively or, worse, as an afterthought (Priyono et al., 2020; Ahmed et al., 2022). This holds particular weight for SMEs, where resource constraints and thinner digital maturity can slow adoption considerably; here, targeted investment in leadership development, talent acquisition, and process redesign appears to matter more, not less (Hai, 2021; Hokmabadi et al., 2024). These observations align closely with the Technology–Organization–Environment (TOE) framework, which has long argued that successful DT depends jointly on technological capability, organizational readiness, and environmental conditions (Matt et al., 2015; Le Viet & Dang Quoc, 2023).

4.5 Sustainability, Marketing, and the Broader Value Proposition of DT

Sustainability considerations also shape DT outcomes in ways worth dwelling on. As Table 4 indicates, firms that weave sustainable practices into their digital initiatives tend to achieve stronger performance across financial, social, and operational dimensions alike (Alojail & Khan, 2023; Bican & Brem, 2020). This tracks with earlier work suggesting that sustainability-oriented DT builds resilience and long-term competitive advantage—partly by reducing resource dependency, partly by strengthening stakeholder trust and regulatory standing (Alghamdi & Al Baity, 2022). Marketing and customer-engagement capabilities add a further dimension: digital technologies amplify these capabilities in ways that let firms harness data analytics for more personalized offerings and more adaptive value creation (Purcrea, 2018; Hokmabadi et al., 2024).

4.6 Cybersecurity as an Inseparable Component of Transformation

It would be a mistake, though, to treat DT's benefits in isolation from its risks. As organizations lean further into digital technologies, their exposure to cyber threats rises correspondingly (Al Shobaki et al., 2022; Saeed et al., 2023). Table 3 suggests that firms with robust cybersecurity governance experience fewer disruptions and sustain stronger stakeholder trust—reinforcing the

idea that security is not a peripheral concern bolted onto DT strategy, but an integral part of it. AI-driven threat detection and preventive security measures appear to help here too, underscoring just how tightly technological innovation and operational resilience are now intertwined (Notaro et al., 2020).

4.7 Industry-Specific Realities

Sectoral differences in DT impact deserve their own mention, if only because they resist easy generalization. In banking, digital initiatives strengthen customer interaction, risk management, and operational efficiency, yet they can also suppress short-term profitability given the scale of upfront investment required (Bareisis & Latimore, 2014; Shanti et al., 2023). Manufacturing tells a somewhat different story: firms benefit from AI-driven automation and predictive maintenance, but only when organizational structures remain flexible enough, and learning mechanisms robust enough, to keep pace with the technology (Gao et al., 2023). Taken together, these sectoral nuances argue for DT strategies that are tailored—genuinely tailored, not just labeled as such—to both technological and contextual constraints (Guo & Xu, 2021).

4.8 Agility and Knowledge Transfer as Connective Mechanisms

Organizational agility and knowledge transfer emerge as essential mediators linking technology adoption to performance outcomes (Ahmed et al., 2022; Al Nuaimi et al., 2021). Firms that manage to disseminate digital competencies effectively, and to institutionalize adaptive processes rather than treat them as one-off initiatives, appear far more likely to convert DT investment into lasting competitive advantage. This shows up clearly in the positive associations between digital platform capability and operational performance across multiple studies (Kitsios & Kamariotou, 2021). The inverse holds too, and perhaps more tellingly: organizations that fail to embed digital knowledge into everyday operational workflows often see diminished returns despite substantial technological spend (Saeed et al., 2023; Al Hleewa & Al Mubarak, 2023).

4.9 Bringing the Threads Together

A few overarching insights emerge once these findings are considered as a whole. First, digital transformation appears most effective when pursued strategically—when

technological adoption is deliberately aligned with leadership vision, process redesign, and sustainability objectives, rather than treated as a series of disconnected initiatives (Alghamdi & Al Baity, 2022; Alojail & Khan, 2023). Second, AI technologies, and AIOps specifically, function less as isolated tools and more as accelerators, enabling the kind of predictive, adaptive operation that measurably improves performance (Andenmatten, 2019; Coronado et al., 2022). Third, organizational and environmental factors—agility, knowledge transfer, sector, regulatory pressure—moderate the relationship between technology adoption and performance in ways that make clear just how context-dependent this phenomenon really is (Priyono et al., 2020; Hai, 2021). And finally, cybersecurity, workforce development, and sustainable practice are not optional extras; they appear, collectively, to determine whether DT investments translate into anything resembling lasting benefit (Al Shobaki et al., 2022; Saeed et al., 2023).

4.10 Concluding Reflection

Pulling all of this together, the discussion points toward a fairly clear conclusion, even if the path to it was anything but linear: digital transformation is not a one-dimensional technological upgrade but a genuinely multi-faceted strategic undertaking. Organizations that integrate AI capabilities thoughtfully, cultivate leadership and digital culture deliberately, embed sustainability principles meaningfully, and manage cybersecurity risk proactively seem best positioned to realize stronger performance, resilience, and competitive advantage over time. Tables 3 and 4 offer the empirical backbone for these conclusions, tracing the key determinants and effect sizes across a genuinely diverse set of organizational contexts. Taken together, these findings contribute both to scholarly understanding of DT as a phenomenon and to practical guidance for managers and policymakers seeking to navigate digital transformation in environments that are, increasingly, defined by rapid technological change.

5. Limitations

Despite the comprehensive scope of this systematic review and meta-analysis, several limitations should be acknowledged. First, the included studies exhibit substantial heterogeneity in terms of research design, industry focus, geographic context, and measurement of digital transformation constructs. As reflected in Tables 3 and 4, variations in effect sizes may stem from differences

in how digital transformation, organizational agility, and performance outcomes are operationalized across studies. While random-effects models were employed to account for this variability, residual heterogeneity cannot be fully eliminated. Second, a significant proportion of the included studies rely on cross-sectional designs, limiting the ability to infer causality between digital transformation initiatives and organizational outcomes. Longitudinal evidence remains comparatively scarce, particularly in emerging domains such as AI-enabled operations and AIOps adoption. Third, potential publication bias may influence the synthesized results, as studies reporting positive or significant effects of digital transformation are more likely to be published than null findings, despite the funnel plot analyses suggesting acceptable symmetry. Finally, although the review spans multiple sectors, SMEs and organizations in developing economies remain underrepresented relative to large enterprises and advanced economies. These limitations suggest caution when generalizing the findings and highlight the need for more longitudinal, sector-specific, and context-sensitive research.

6. Conclusion

This systematic review and meta-analysis suggest, fairly convincingly, that digital transformation enhances organizational agility, operational performance, and resilience—but only when it is aligned with leadership commitment, AI capability, and genuine organizational readiness. What emerges most clearly, perhaps, is that DT resists treatment as a one-time technological upgrade; it behaves instead like a continuous, context-dependent process that unfolds differently depending on firm size, sector, and digital maturity. Organizations that integrate artificial intelligence thoughtfully, cultivate cultures capable of adapting rather than merely complying, and fold sustainability and cybersecurity considerations into their digital strategies from the outset appear best positioned to convert technological investment into lasting competitive advantage. None of this happens automatically, and none of it happens quickly. Still, the evidence gathered here offers a reasonably solid foundation—both for researchers seeking to refine theoretical models of DT, and for practitioners trying to translate that theory into decisions that actually hold up across diverse organizational contexts.

Author Contributions

A. conceptualized the study, designed the review protocol, and developed the research framework. A. and M.A. conducted the literature search, study selection, data extraction, quality assessment, and evidence synthesis. M.A. performed the systematic review, meta-analysis, and statistical interpretation and drafted the original manuscript. M.A. contributed to data validation, interpretation of findings, critical revision of the manuscript, and refinement of the theoretical and practical implications. Both authors reviewed and approved the final manuscript and agreed to be accountable for all aspects of the work.

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