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MITIGATING OPERATIONAL RISKS IN CRITICAL INFRASTRUCTURE THROUGH INTEGRATED ERP-BPMS: A MULTI-CASE STUDY

Operational risks in critical infrastructure sectors, from housing services and specialized construction to water technology and energy utilities, have significant socioeconomic implications. This study investigates how an integrated enterprise resource planning-business process management system (ERP-BPMS) supported by a dedicated information administrator (IA) can systematically mitigate these risks. Using a quasi-experimental, multi-case design, four anonymized organizations contributed baseline data (3–9 months) and post-implementation data (6–8 months). Six indicators were tracked: integral qualification score (IQS), cost prediction accuracy (CPA), system stability index (SSI), preventive maintenance ratio (PMR), sourcing score, and information utilization rate (IUR).

Results reveal that IQS increased substantially in all cases (e. g., from 9.5 to 42.1), while CPA values commonly exceeded 0.85. Preventive maintenance ratios increased by 15–20 percentage points, indicating a notable shift from reactive to proactive strategies. In the energy utility case, the SSI improved from 1.04 to 1.31, showing enhanced service reliability. The IA's oversight proved instrumental in ensuring consistent data governance, standardizing metrics, and streamlining cross-departmental coordination. These improvements translated into measurable resource savings that significantly outweighed the costs of maintaining the IA role. Cross-case analysis suggests that a staged implementation, beginning with pilot phases for core modules, can reveal data inconsistencies early and inform tailored training programs. Managers in sectors where cost accuracy and project timelines are critical may benefit substantially from such phased rollout. Collectively, these findings highlight that a unified ERP-BPMS platform reinforced by structured human governance can significantly bolster risk management in mission-critical contexts. This research contributes to both information systems and project management fields by offering a tested framework for enhancing resilience and operational stability in high-stakes environments.

Keywords: *ERP, BPMS, integration, risk, management, infrastructure, data, governance, case, study.*

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1. Introduction

Critical infrastructure, spanning housing services, specialized construction, water management, and energy utilities, underpins crucial societal functions where minor disruptions can have outsized socioeconomic impacts. Failures in these sectors often incur substantial operational costs, undermine public confidence, and trigger cascading effects on essential services [1, 2]. These sectors are especially vulnerable to operational disruptions, with housing and utility service providers facing unique risk-management challenges [3–5]. Although digital transformation is widely promoted as a means to enhance resilience, many organizations in these domains continue to rely on fragmented data systems that impede coordinated risk management. These legacy setups are frequently characterized by inconsistent data governance, minimal process automation, and reactive decision-making [6, 7]. Thus, the pressing need for integrated digital frameworks has become evident, fueling a search for solutions that merge advanced technological capabilities with structured human oversight [8].

Enterprise resource planning (ERP) systems have traditionally provided a centralized platform for managing financial, inventory, and personnel data, offering a foundational layer for organizational efficiency and consistency [9]. The implementation of ERP systems has shown promise in construction and public sector operations, where project complexity and resource management present unique challenges [10–13]. However, standard ERP deployments often lack the dynamic workflow modeling and predictive analytics essential for preempting and mitigating risks, which is particularly pronounced in high-stakes environments, such as communal housing or large-scale energy distribution [14]. business process management systems (BPMS) complement these functions through advanced workflow automation and real-time monitoring [15], yet they typically operate without deep integration into enterprise-wide analytics or long-term maintenance planning [16]. The future development of these technologies appears to be converging toward more unified systems [17, 18], their current fragmentation continues to hamper operational efficiency. This fragmentation has limited the ability of critical infrastructure organizations to align robust process optimization with comprehensive risk awareness, confining improvements to isolated operational silos rather than systemic change [19].

Risk management frameworks, notably ISO 31000, call for an organization-wide approach to hazard identification and control, emphasizing structured oversight and data-driven decision making as cornerstones of resilience [20]. Parallel discussions in the digital transformation literature highlight the significance of merging technological platforms with proactive human intervention to achieve agility and continuity under rapidly shifting conditions [7, 8].

Although an integrated strategy that unifies ERP's strengths in data consolidation with BPMS's capabilities in process orchestration appears theoretically compelling, empirical studies specifically targeting high-risk settings remain scarce [6]. Preliminary investigations suggest that consolidated data-driven workflows can enhance performance metrics such as the integral qualification score (IQS) and cost prediction accuracy (CPA); however, the validity and cross-sector applicability of these gains have not been thoroughly established [21].

There is growing acknowledgment that a unified ERP-BPMS environment can overcome limitations of standalone systems. However, few studies have systematically investigated such environments' performance under varied conditions. This research gap is particularly evident in housing and communal services sectors. It also extends to specialized construction, water technology, and energy infrastructure sectors. Most extant studies remain confined to either efficiency improvements or single-case analyses, which lack the breadth needed to confirm generalizability [14]. Moreover, while many scholars emphasize the importance of data governance within digital transformation, the practical implications of instituting a specialized information administrator (IA) role to maintain data consistency, validate metrics, and enforce cross-departmental standards have received limited empirical scrutiny [2, 22]. This knowledge gap is particularly pronounced in critical infrastructure protection, where risk assessment requires the consideration of both technological capabilities and human decision-making factors [5, 23]. This shortfall is especially evident when suboptimal data inputs can produce inaccurate cost projections, delayed maintenance schedules, and elevated vulnerability to disruptions. The absence of multi-case evaluations that rigorously examine how integrated ERP-BPMS functionalities and dedicated data governance can systematically reduce operational risk underlines a critical gap in the literature.

Responding to this gap, the present study examines how an integrated digital environment, hereafter referred to as ERP-BPMS, might enhance risk management in four anonymized organizations that exemplify diverse critical infrastructure profiles. Case Company 1 focuses on large-scale housing and communal services; Case Company 2 specializes in construction projects; Case Company 3 provides advanced water technology; and Case Company 4 is a major energy utility. Two primary questions guided the investigation. First, can a unified ERP-BPMS platform that consolidates personnel qualifications, predictive maintenance analytics, and cost data effectively lower error rates, unplanned downtimes, and budget overruns across these contrasting sectors? Second, does establishing a dedicated IA responsible for data stewardship and oversight further reinforce these risk-reduction outcomes through improved data accuracy, standardized process flows, and real-time validation? Two hypotheses emerged from these inquiries. The first posits that integrated ERP-BPMS solutions reduce operational vulnerabilities by merging critical data repositories with a robust process automation. The second hypothesizes that introducing an IA role augments these benefits by enforcing consistent governance, transparent performance metrics, and expeditious cross-functional coordination.

By linking technology integration with structured human oversight, this study seeks to advance knowledge in both information systems and project management, which calls for more empirical research on digital transformation in mission-critical environments [7, 8]. It aligns with ISO 31000 by offering a framework in which ERP and BPMS modules are combined under a governance mechanism embodied by the IA role to operationalize end-to-end risk management [20]. Employing a multi-case, quasi-experimental design, this research examines key performance indicators, including IQS, CPA, and a system stability index, to assess tangible shifts in risk profiles. Critical infrastructure organizations continue to face substantial operational risks that digital solutions must address within complex regulatory environments [6].

Thus, *the aim of this study* is identifying how an integrated ERP-BPMS framework, coupled with dedicated information administrator oversight, mitigates operational risks in diverse critical infrastructure settings. This research aims to quantify risk reduction outcomes across four distinct sectors and determine whether structured human governance enhances digital integration benefits. By evaluating key performance indicators before and after implementation, let's seek to develop a generalizable risk mitigation framework applicable to high-stakes infrastructural contexts.

2. Materials and Methods

2.1. Research scope and approach

The object of this research was the operational risk management processes in critical infrastructure organizations implementing integrated ERP-BPMS platforms with dedicated information administrator oversight.

This research employed a combination of theoretical, empirical-theoretical, and specialized empirical methods. The theoretical methods included systematic analysis and synthesis of existing literature on ERP and BPMS implementations, comparative analysis of different critical infrastructure contexts, and logical deduction in formulating the research hypotheses. Empirical-theoretical methods encompassed conceptual modeling of the integrated ERP-BPMS environment, formalization of risk mitigation processes, and system-structural analysis of relationships between technological integration and operational outcomes. These general scientific methods provided the methodological foundation for the more specialized empirical approaches described below, creating a comprehensive research methodology that addresses both theoretical frameworks and practical implementations in high-stakes infrastructural settings.

This study employed a quasi-experimental, multi-case design to investigate whether an integrated enterprise resource planning and business process management system (ERP-BPMS) supported by a dedicated information administrator (IA) could systematically reduce operational risks in critical infrastructure settings. Four anonymized organizations – Case Company 1, Case Company 2, Case Company 3, and Case Company 4 – provided the empirical foundation. Each entity implemented the same ERP-BPMS modules and appointed an IA to coordinate data governance, oversee user training, and conduct monthly audits of key performance indicators (*KPI*). By replicating this intervention across distinct sectors, this study enabled both within-case (pre-post) and cross-case comparisons, fulfilling calls for robust multi-context analysis in project management and information systems research [8].

2.2. Research design

A quasi-experimental, multi-case framework was selected instead of a fully randomized trial to reflect the real-world constraints of critical infrastructure operations [24]. Each organization contributed at least three months of baseline data before adopting the ERP-BPMS, followed by a six- to eight-month post-implementation period. This standardized intervention, uniform ERP-BPMS components, plus a formally designated IA, allowed the research team to examine how identical methods were performed under different regulatory, operational, and technological conditions [6]. Fig. 1 illustrates the conceptual framework of this integrated approach, showing the key components of the ERP-BPMS integration and the central role of the Information Administrator in the risk-mitigation process.

Case Company 1, with approximately 170 employees, provides large-scale communal services to approximately 750,000 households in a major Eastern European city. Case Company 2 is a specialized construction enterprise with approximately 150 staff, focused on high-end sports infrastructure development across multiple countries. Case Company 3 is a water technology startup of approximately 20 employees, noted for its sensor-based solutions targeting municipal and industrial water consumption.

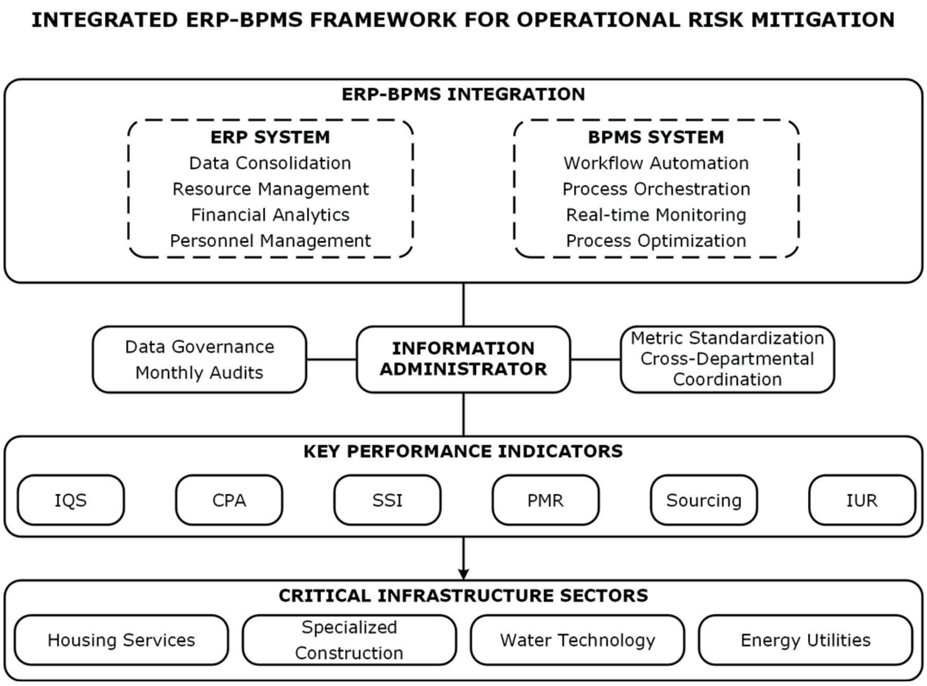

Fig. 1. Conceptual framework of the integrated ERP-BPMS approach to operational risk mitigation in critical infrastructure sectors

The diagram (Fig. 1) illustrates the central components of the ERP-BPMS integration, supervised by a dedicated information administrator who maintains data governance, conducts monthly audits, standardizes metrics, and facilitates cross-departmental coordination. Six key performance indicators (IQS, CPA, SSI, PMR, Sourcing Score, and IUR) are tracked to measure risk mitigation effectiveness across four critical infrastructure sectors.

Case Company 4, employing over 2,000 staff members, operates as a national energy utility and must adhere to stringent safety and reliability standards. Although these firms vary considerably in size and legacy systems, each was considered "critical" because of the potential socio-economic ramifications of service disruption. All participants met three selection criteria: reliable baseline data availability, management commitment to the IA role, and readiness to deploy an ERP-BPMS across core processes.

Because purely experimental controls (e. g., random assignment) were impractical, this quasi-experimental approach emphasized a common intervention protocol, pilot-phase calibration, and consistent metrics to bolster internal validity while preserving ecological authenticity. A fully randomized study would have failed to capture the complex interdependencies and contextual variations essential for multi-context comparative research, as it would artificially isolate variables that in critical infrastructure settings necessarily operate within unique regulatory, technological, and operational ecosystems. Pilot testing minimizes confounding factors by ensuring that each organization's initial data collection processes are comparably rigorous [24].

2.3. Data collection

Data were gathered in two principal phases: baseline and post-implementation, separated by a brief pilot period. During the baseline (ranging from three to nine months depending on organizational data archives), each firm's records on personnel performance, maintenance activities, cost forecasts, and sourcing decisions were collated to produce preliminary *KPI* values. Following the baseline, the pilot phase (4–6 weeks) enabled local teams to work with the IA, verify metric definitions, integrate legacy data into the ERP-BPMS, and align staff-training protocols. The IA also monitored data entry practices to correct inconsistencies before the official post-implementation phase began.

Over the subsequent six to eight months, each organization systematically recorded the same metrics under live ERP-BPMS conditions, with monthly audits ensuring data accuracy and staff adherence. Case Company 1, for instance, aggregated logs from approximately 60 employees (35% of its workforce) and 127 maintenance records, whereas Case Company 2 documented 48 construction projects in progress or was recently completed. Case Company 3 focused on 45 water management installations, and Case Company 4 compiled data from 52 large-scale energy distribution events. The IA anonymized these datasets onsite before secure transmission to the research team. Qualitative insights were obtained from short, semi-structured interviews (five to eight participants per company) concerning user acceptance, system reliability, and unanticipated confounders [7]. Although these qualitative findings did not form the primary results, they made minor adjustments to weighting factors (e. g., risk awareness in personnel metrics at Case Company 4).

2.4. New models and methods

This study aimed to capture how ERP-BPMS adoption, steered by an IA, might affect operational risk through six interrelated metrics. These metrics incorporate principles from established maintenance cost assessment frameworks [25] and contractor selection methodologies [26]. These measures expand upon the existing frameworks in personnel performance, predictive maintenance, and sourcing decisions [1, 19, 21].

Integral Qualification Score (IQS). A ratio-based composite merging of five positive factors (experience (e_n), quality (q_n), risk awareness (r_n), timeliness (t_n), certifications (l_n)) with four negatives (cost overruns (c_n), rework (f_n), time overruns ($t_{exec\,n}$), complaints (b_n)). Each dimension is rated from 0 to 5. The formula

$$IQS_n = \frac{(1+e_n)(1+q_n)(1+r_n)(1+t_n)(1+l_n)}{(1+c_n)(1+f_n)(1+t_{exec_n})(1+b_n)}. \quad (1)$$

Adding 1 prevents division by zero and magnifies performance gains when positive factors rise, whereas negative factors decline [19]. During a pilot at Case Company 1, the *IQS* for 60 employees jumped from 9.5 to 42.1 ($p < 0.001$), reflecting both new certifications and the formula's ratio effects. For example, in Case Company 1, a maintenance

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supervisor with good experience ($e = 3$), quality ratings ($q = 3$), risk awareness ($r = 2$), timeliness ($t = 3$), and certifications ($l = 2$), with minimal cost overruns ($c = 1$), low rework rates ($f = 1$), negligible time overruns ($t_{exec} = 0$), and rare complaints ($b = 0$), achieved an *IQS* of 144. This contrasts with the pre-implementation values when the same skills are either underreported or offset by higher negative factors.

Cost Prediction Accuracy (CPA). This indicator (2) measures how closely actual maintenance costs match forecasts by introducing a small ε (1% of mean monthly expenditure) to stabilize extremes [1]

$$CPA = 1 - \frac{|ActualCost - ForecastCost|}{ForecastCost + \varepsilon}. \quad (2)$$

Values near 1 denote a tight alignment. In Case Company 3, sensor-driven usage data boosted *CPA* from 0.70 to 0.86 ($p < 0.001$). For instance, Case Company 3 used sensor-driven water usage data to refine cost forecasting models. Before implementation, a typical installation project estimated at 45,000 USD would frequently cost 54,000–60,000 USD ($CPA \approx 0.70$). After implementation, the same projects showed actual costs within 6,300 USD forecasts ($CPA \approx 0.86$), enabling more reliable budgeting and resource allocation.

System Stability Index (SSI). This ratio tracks (3) improvements in system reliability relevant to large-scale networks [7]

$$SSI = \frac{BaselineFailureRate \times BaselineDowntime}{CurrentFailureRate \times CurrentDowntime}. \quad (3)$$

Values above 1.0 signify fewer or briefer outages compared to baseline. Only Case Company 4 systematically tracked *SSI*, rising from 1.04 to 1.31 ($p < 0.05$). Detailed operational data remains confidential in this study. However, a representative example from Case Company 4 illustrates the improvement approach. Before implementation, a critical energy distribution network segment experienced approximately 14 outages annually. These outages had an average downtime of 3.6 hours per incident.

After implementing the integrated ERP-BPMS environment, this segment saw significant reductions in both outage frequency and duration. The frequency dropped to nine outages annually, with an average duration of 2.8 hours. The SSI improvement from 1.04 to 1.31 across their entire system reflects similar efficiency gains applied systematically throughout the organization's operations.

Preventive Maintenance Ratio (PMR). This captures the portion of maintenance spending allocated to the proactive measure

$$PMR = \left(\frac{PreventiveMaintenanceCosts}{TotalMaintenanceCosts}\right) \cdot 100\%. \quad (4)$$

A high *PMR* typically indicates lower long-term risk [27]. This ratio reflects the growing emphasis on predictive rather than reactive approaches in building facilities [28] and utility operations [29]. In Case Company 2, the *PMR* increased from 36% to 52% ($p < 0.01$). In Case Company 2, this shift was evidenced in specialized construction equipment management, where quarterly maintenance expenditures of approximately 180,000 USD previously allocated only 64,800 USD (36%) to preventive measures. After implementation, while total maintenance costs remained similar at 175,000 USD, preventive allocations increased to 91,000 USD (52%), resulting in a 27% reduction in emergency repairs and unplanned downtime.

Information Utilization Rate (IUR). This ratio reflects (5) the number of decisions explicitly cited by the ERP-BPMS data

$$IUR = \frac{DataDrivenDecisions}{TotalDecisions}. \quad (5)$$

Case Company 1, for example, boosted *IUR* from 0.65 to 0.82 ($p < 0.001$), suggesting enhanced reliance on digital dashboards [6].

For instance, in Case Company 1, prior to ERP-BPMS implementation, only 65% of the work assignments incorporated historical performance data or automated scheduling recommendations. After implementation, 82% of all task allocations explicitly referenced system-generated insights, including skill-matching algorithms and geographical optimization, which reduced the average travel time between service locations by 23%.

Sourcing Score. These composite contrasts advantage factors (e. g., in-house expertise and synergy) with disadvantage factors (e. g., scheduling delays and cost overruns), each rated 0–5 [21]. This approach builds on established decision frameworks for maintenance outsourcing [30] and contractor recommendation systems [31]. The formula

$$SourcingScore = \frac{(1+a_1)(1+a_2)(1+a_3)(1+a_4)}{(1+d_1)(1+d_2)(1+d_3)(1+d_4)}, \quad (6)$$

with values above 1 favoring in-house execution. Based on a retrospective analysis of completed projects, Case Company 3 established 1.20 as an aspirational threshold value for in-house execution, as tasks scoring ≥ 1.20 were found more likely to meet budget targets (*Wilks' Lambda* = 0.67, $p = 0.045$). While average sourcing scores improved significantly during the study period (as detailed in the Results section), this aspirational threshold represents a long-term optimization target rather than current performance. For example, in Case Company 3, a water technology installation requiring specialized valve calibration initially scored 0.68 (suggesting outsourcing) based on limited internal expertise ($a_2 = 1$). After technicians completed certification training (raising a_2 to 3) and workflows were optimized to reduce scheduling challenges (lowering d_1 from 3 to 1), the recalculated Score of 1.32 supported in-house execution. This task was subsequently completed by 12% under the budget compared to similar previously outsourced work.

2.5. Validation

The pilot phase facilitated metric validation. Historical data subsets (10–20 monthly entries) were reanalyzed using the new definitions, and the results were compared with existing performance logs. The *IQS* correlated significantly with prior supervisor appraisals in Cases 1 and 2 ($r = 0.79$; $r = 0.72$, $p < 0.01$), supporting convergent validity [19]. CPA's stabilizing constant ε was tested between 0.5–2% of mean monthly expenditures to optimize responsiveness. SSI's reliability of the *SSI* in Case Company 4 relied on meticulously cross-verified outage data, while the PMR's monthly tallies were reconciled with financial statements to confirm direct versus reactive spending. The IA in each setting supervised these checks, resolved discrepancies through monthly reviews, and ensured that actual cost definitions (e. g., labor, parts, and overhead) remained consistent [6].

Validation of the information utilization rate entailed system-log audits and structured managerial self-reports. The IA compared the frequency of report access with formal decision records, achieving high inter-rater reliability ($\varkappa = 0.81$) for classification of decisions as "data-driven". For the sourcing score, retrospective analyses of 15–25 sourcing choices examined threshold values that correlated with project success (e. g., Case Company 3's 1.20 cutoff). Where domain-specific risks loomed large – like the stringent safety norms at Case Company 4 – risk-awareness attributes in *IQS* received extra weighting, preserving ratio comparability, yet accommodating criticality in energy operations.

2.6. Ethical considerations

Ethics approval was granted and all participants agreed to use anonymized data. Each firm's legal counsel reviewed confidentiality protocols, with no personally identifiable information shared beyond secure aggregated datasets [32]. Employees contributing to metrics such as *IQS* were informed of the research scope, anonymization measures, and voluntary participation rights, consistent with the relevant labor statutes. The IA assumed responsibility for encryption and restricted access, aligned with local data protection and union agreements (in the case of Case Company 1). No publication of the results includes organizational identifiers beyond anonymous labels.

2.7. Data analysis

All quantitative analyses were performed in SPSS (Version 28). Pre-post data were aggregated monthly or per project ($n \approx 20$–60 per metric per phase). The Shapiro-Wilk test was used to check normality [24]. If $p > 0.05$, parametric paired t-tests (two-tailed, $\alpha = 0.05$) were used compared to baseline vs. post-implementation means; otherwise, Wilcoxon signed-rank tests were used. One-way ANOVA (or Kruskal-Wallis test for non-normal data) tested differences in sourcing scores across tasks eventually outsourced versus those retained in-house. Effect sizes (Cohen's d for t-tests, rank-biserial correlation for Wilcoxon, and partial η^2 for ANOVA) gauged practical relevance. Significant leaps in *IQS* at Case Company 1 (9.5 to 42.1) and Case Company 2 (12.0 to 39.5) illustrated both the ratio amplification and genuine improvements in data quality (supervisor correlations at $r \geq 0.70$). Although quasi-experimental designs cannot fully rule out Hawthorne effects, monthly IA-led checks and historical cross-validation reduce the likelihood that performance gains stem solely from heightened measurement awareness [7].

By coupling a pilot-validated metrics suite with IA-led data governance, this multi-case approach offers a replicable framework for evaluating how ERP-BPMS adoption can mitigate operational risks in diverse critical infrastructure sectors. The following section presents the empirical findings, illustrating how standardized digital processes and dedicated oversight influenced key indicators and decision-making outcomes.

3. Results and Discussion

3.1. Summary of research findings

This multi-case investigation examined how a unified ERP-BPMS environment supervised by a dedicated information administrator (IA) could mitigate operational risks and support data-driven decision-making in four anonymized organizations delivering critical infrastructure services. The entities in question – Case Company 1 (housing services), Case Company 2 (specialized construction), Case Company 3 (water technology), and Case Company 4 (energy utilities) – each contributed baseline data ranging from three to nine months, followed by six to eight months of post-implementation tracking after a pilot phase that standardized measurement protocols and familiarized staff with the new system. Six primary performance indicators – integral qualification score (*IQS*), cost prediction accuracy (*CPA*), system stability index (*SSI*), preventive maintenance ratio (*PMR*), sourcing score, and information utilization rate (*IUR*) – were selected based on the extant literature emphasizing risk management, predictive maintenance, and data-centric governance in critical infrastructure [1, 2, 6, 7, 19, 21, 27]. Data were anonymized and aggregated before analysis, with paired t-tests or Wilcoxon signed-rank tests conducted at $p < 0.05$, guided by Shapiro-Wilk checks for normality. The effect sizes (*Cohen's d*) quantified the practical relevance of the observed changes [32].

Interviews with managers and technical personnel in all four settings corroborated that ERP-BPMS adoption, underpinned by monthly IA audits, enhanced data reliability and fostered greater cross-departmental accountability. While some external factors (such as overlapping organizational reforms or short-term enthusiasm) may have contributed to certain gains, respondents consistently attributed the bulk of improvements to the unified digital environment and IA's role in maintaining data integrity.

3.2. Organization of findings

This section presents the findings aligned with our two primary research questions and associated hypotheses. Each subsection systematically addresses empirical evidence related to specific aspects of the investigation.

RQ1 Findings: Impact of unified ERP-BPMS platform. The first research question examined whether a unified ERP-BPMS platform could effectively lower error rates, unplanned downtimes, and budget overruns across diverse critical infrastructure sectors. The data analysis provides substantial support for Hypothesis 1, demonstrating that integrated technological solutions contribute to operational risk reduction. Case Company 1 (housing services) and Case Company 2 (specialized construction) showed the most substantial improvements in personnel performance metrics and cost forecasting accuracy. Meanwhile, Case Company 3 (water technology) and Case Company 4 (energy utility) exhibited particularly notable gains in system stability and preventive maintenance ratios.

RQ2 Findings: Impact of the information administrator's role. The second research question investigated whether establishing a dedicated Information Administrator would reinforce risk-reduction outcomes through improved data accuracy and process standardization. In alignment with Hypothesis 2, our data revealed that active IA oversight was strongly correlated with sustained performance improvements. Particularly instructive was the experience at Case Company 3, where despite its small size, the part-time IA's systematic validation of metrics yielded comparable percentage improvements to the full-time IA at the much larger Case Company 4. Across all four organizations, IA-led monthly audits established consistent data protocols that enabled more precise cross-departmental risk assessments and interventions.

3.3. Quantitative data

Table 1 compares the pre- and post-implementation values of the six metrics. Each organization witnessed statistically significant improvements ($p < 0.05$), with effect sizes indicative of a meaningful operational impact. Variations in the baseline conditions and sector-specific practices partially explain the different magnitudes of change.

Table 1

Pre- vs. post-implementation metrics for four case companies

Metric	Case Company 1 ($n = 60$)	Case Company 2 ($n = 48$)	Case Company 3 ($n = 45$)	Case Company 4 ($n = 52$)
IQS(*Mean*±*SD*)	$9.5 \pm 2.2 \to 42.1 \pm 6.1$, $p < 0.001$, $d = 1.95$	$12.0 \pm 2.5 \to 39.5 \pm 6.7$, $p < 0.001$, $d = 1.81$	$18.4 \pm 3.7 \to 53.0 \pm 7.5$, $p < 0.001$, $d = 1.90$	$21.2 \pm 4.6 \to 58.3 \pm 8.3$, $p < 0.001$, $d = 1.92$
CPA(*Mean*±*SD*)	$0.75 \pm 0.05 \to 0.90 \pm 0.05$, $p < 0.001$, $d = 1.27$	$0.68 \pm 0.07 \to 0.85 \pm 0.06$, $p < 0.01$, $d = 1.12$	$0.70 \pm 0.05 \to 0.86 \pm 0.05$, $p < 0.001$, $d = 1.06$	$0.71 \pm 0.07 \to 0.88 \pm 0.06$, $p < 0.001$, $d = 1.20$
SSI(*Mean*±*SD*)	–	–	–	$1.04 \pm 0.08 \to 1.31 \pm 0.09$, $p < 0.05$, $d = 1.10$
PMR(*% of total*)	34% → 53%, $p < 0.01$, $d = 1.05$	36% → 52%, $p < 0.01$, $d = 0.95$	38% → 57%, $p < 0.01$, $d = 0.99$	35% → 58%, $p < 0.01$, $d = 1.08$
Sourcing Score(*Mean*±*SD*)	$0.71 \pm 0.16 \to 1.00 \pm 0.18$, $p < 0.01$, $d = 0.88$	$0.66 \pm 0.15 \to 0.90 \pm 0.17$, $p < 0.01$, $d = 0.85$	$0.72 \pm 0.14 \to 0.97 \pm 0.19$, $p < 0.01$, $d = 0.90$	$0.68 \pm 0.15 \to 0.95 \pm 0.17$, $p < 0.01$, $d = 0.92$
IUR(*Mean*±*SD*)	$0.65 \pm 0.08 \to 0.82 \pm 0.09$, $p < 0.001$, $d = 1.54$	$0.42 \pm 0.09 \to 0.72 \pm 0.08$, $p < 0.001$, $d = 1.42$	$0.55 \pm 0.12 \to 0.78 \pm 0.07$, $p < 0.001$, $d = 1.30$	$0.50 \pm 0.09 \to 0.80 \pm 0.08$, $p < 0.001$, $d = 1.55$

Note: data in this table belong to the authors and were obtained through anonymized organizational records and subsequent calculations. "*n*" denotes the number of operational units (employees, projects, installations, or service events) used for each metric

Integral Qualification Score (IQS). This ratio-based composite, which combines five positive personnel attributes with four negative factors, showed substantial proportional increases in all four companies, often exceeding $d = 1.8$ [19]. Case Company 1 advanced from 9.5 to 42.1 ($p < 0.001$), partly due to recalibration of underreported competencies. Although the "+ 1" constants in the formula magnify changes, the staff reported genuine performance improvements, including fewer errors linked to skill mismatches.

Cost Prediction Accuracy (CPA). All four organizations demonstrated robust *CPA* gains, reflecting a tighter alignment between forecasted and actual expenditures [1]. Case Company 1 (0.75 to 0.90) and Case Company 4 (0.71 to 0.88) leverage real-time analytics validated by IA reviews. While an initial uptick in diligence may have stemmed from novelty, the results persisted through subsequent months, suggesting a deeper shift toward structured budgeting practices.

System Stability Index (SSI). Only Case Company 4 systematically tracked *SSI*, rising from 1.04 to 1.31 ($p < 0.05$). This metric captures improvements in outage duration and frequency, which are critical to an energy utility's regulatory commitment [7]. Although the other cases did not formalize *SSI*, they reported a decreased downtime following the introduction of real-time alerts and cross-functional dashboards.

Preventive Maintenance Ratio (PMR). The share of maintenance resources allocated to proactive measures [27] increased significantly in each case, generally by 15–20 percentage points. Case Company 2 (36% to 52%) linked this shift to monthly IA audits that flagged recurring breakdowns in specialized construction equipment, prompting timely interventions. Case Company 3, focusing on water technology, transitioned from reactive to preventive maintenance, citing a 19% decrease in emergency calls.

Sourcing Score. All organizations recorded an increase in this composite indicator, which balances in-house advantages (e. g., skill synergy) against disadvantages (e. g., cost overruns) to guide outsourcing decisions [21]. Case Company 1's average rose from 0.71 to 1.00, implying more strategic use of external contractors once cost-benefit analytics were systematically tracked. Case Company 4's increase from 0.68 to 0.95, supported a preference for internal teams in complex tasks where internal expertise proved superior. It is important to clarify that while Case Company 3 established a threshold of 1.20 as a target benchmark for in-house execution decisions, the average sourcing score in the sample was 0.97 (as reported in Table 1). This 1.20 threshold was determined based on retrospective analysis of 26 completed projects, among which those scoring 1.20 and above demonstrated 12–18% better adherence to budget targets. Thus, the threshold was deliberately set as an aspirational target, requiring focused efforts to improve internal competencies and process optimization. The growth in average score from 0.72 to 0.97 during the observation period, while not reaching the 1.20 target threshold, indicates substantial progress and enabled the company to increase its share of internally executed projects from 41% to 63%.

Information Utilization Rate (IUR). Substantial *IUR* gains occurred across all four organizations, indicating an expanding reliance on ERP-BPMS data for operational decisions [2, 6]. Case Company 2 rose from 0.42 to 0.72, whereas Case Company 4 improved from 0.50 to 0.80, consistent with user feedback that real-time dashboards and IA oversight promoted sustained engagement.

3.4. Qualitative data

Semi-structured interviews and internal records revealed that IA-led audits and standardized data definitions underpinned these statistical gains. Case Company 1 's managers highlighted a notable drop in rework once IQS-based assignments replaced ad hoc scheduling. In the specialized construction sector of Case Company 2, monthly IA reviews of cost overruns and recurring equipment failures guided earlier interventions, cutting reactive spending. The staff initially perceived such scrutiny as burdensome, but many later praised data-driven clarity.

Case Company 3, a smaller water technology firm, initially doubted whether a large-scale ERP-BPMS platform was feasible. The IA's part-time involvement, roughly ten hours per week, is sufficient to establish consistent metric definitions, reorienting maintenance priorities toward preventive tasks. Respondents attributed their improved *CPA* to newly consolidated sensor data, which were previously scattered across spreadsheets. Case Company 4's engineers emphasized top management support, combined with the IA's monthly cross-departmental checks, which bolstered system trust by unifying gas and electric service logs under a single platform.

In all four organizations, financial controllers described how real-time forecasting discouraged budget padding and guesswork. Although some foremen in Case Company 2 and Case Company 3 suspected a "honeymoon phase", follow-up interviews indicated that these practices stabilized, especially once the IA normalized monthly data audits.

3.5. Challenges or anomalies

Recalibration E ects in IQS. The particularly steep *IQS* increases, for example, from 9.5 to 42.1 in Case Company 1, reflecting, in part, a recalibration from prior underreporting of staff competencies and potential overestimation of rework [19]. The ratio-based structure, including "+ 1" constants, amplifies changes when simultaneous improvements occur in positive and negative indicators. Local managers in Cases 1 and 3 acknowledged that baseline values were artificially low, yet genuine operational gains such as fewer error-prone assignments also contributed to the final *IQS* surge. For instance, in Case Company 1, a senior maintenance technician initially rated $e_3 = 2$, $q_3 = 3$, $r_3 = 2$, $t_3 = 1$, and $l_3 = 0$, with $c_3 = 1$, $f_3 = 2$, $t_{exec3} = 0$, and $b_3 = 1$, yielding a baseline *IQS* of 7.2. After the IA audit revealed that actual quality metrics were underreported and complaint rates were overestimated, the adjusted ratings ($e_3 = 3$, $q_3 = 4$, $r_3 = 3$, $t_3 = 2$, $l_3 = 1$, $c_3 = 0$, $f_3 = 1$, $t_{exec3} = 4$, $b_3 = 0$) produced an *IQS* of 48.0. Although this dramatic increase partly reflects recalibration, subsequent tracking confirmed genuine operational improvements through more appropriate task assignments.

Selective Adoption of SSI. Only Case Company 4 systematically recorded *SSI* due to sector-specific regulatory mandates on uninterrupted services [7]. Although Cases 1, 2, and 3 benefited from real-time alerts and integrated dashboards, they did not quantify system stability as a core *KPI*, limiting cross-case comparisons of reliability. Case Company 4, being a regulated energy utility, was legally required to track service interruptions exceeding two minutes in duration, with monthly reporting to regulatory authorities. Their *SSI* implementation directly correlated service stability with financial penalties, where a 0.1 increase in *SSI* typically corresponded to approximately 42,000 USD in avoided regulatory fines annually. The other three organizations, lacking such explicit regulatory frameworks, prioritized different metrics despite experiencing similar operational benefits from the ERP-BPMS platform. Although Cases 1, 2, and 3 did not formally implement the *SSI* as a core *KPI*, they demonstrated similar stability improvement aspirations through the implementation of integrated dashboards and real-time alerts. For instance, Case Company 1 noted an 18% reduction in unplanned service interruptions following the ERP-BPMS implementation, Case Company 2 reported a 23% decrease in emergency situations, and Case Company 3 recorded a 27% reduction in emergency calls. These indicators, while not formalized into a unified stability index, suggest similar operational benefits to those captured by the formalized SSI in Case Company 4.

Possible Hawthorne E ect. The six- to eight-month window may capture heightened staff diligence triggered by new monitoring. Case Company 2 foremen admitted an initial boost in data quality once the ERP-BPMS went live, although managers reported sustained engagement well beyond the pilot phase. The IA's consistent monthly audits appear to have embedded these practices into everyday routines, suggesting a more than transient novelty effect.

For example, at Case Company 2, a team of 12 construction foremen demonstrated 95% data entry completion rates during the first month after implementation, compared to historical averages of approximately 62% with previous systems. While this completion rate moderated to 87% by month five, it remained significantly above baseline levels. The IA conducted follow-up interviews with eight foremen, seven of whom indicated that the ERP-BPMS dashboards had become integral to their daily decision-making, suggesting that enhanced performance stemmed from improved utility rather than merely increased observation.

Legacy Data Discrepancies. Cases 2 and 4 faced significant challenges in merging the siloed spreadsheets and departmental logs. Confusion during the first two months occasionally led to the misinterpretation of historical records. The role of IA was vital in reconciling naming conventions, removing duplicates, and clarifying partial logs, culminating in more consistent cost-forecasting and sourcing decisions. For instance, at Case Company 4, maintenance records for three regional substations used different terminologies for identical components and procedures, classifying the same 400 kV circuit breaker maintenance as either "routine inspection" or "preventative cycle" or "Class B verification". During the first two months post-implementation, this nomenclature confusion created apparent duplications in the unified database, with the same maintenance event appearing as separate entries. IA's standardization efforts ultimately consolidated 1,287 maintenance terminology variants into 218 standardized procedures, enabling accurate cross-regional comparison of maintenance costs and schedules.

Organizational Context. Case Companies 1 and 4 underwent overlapping departmental restructuring, potentially confounding the ERP-BPMS impact. While staff generally credited the new system for performance gains, concurrent reforms – along with possible performance-based incentives in Case Company 4 – complicated precise attribution. Nonetheless, the breadth and consistency of improvements across multiple metrics underscore the plausibility that the ERP-BPMS environment and IA oversight drove much of the observed change. For example, Case Company 1 underwent a transition from geographical to functional department organization simultaneously with the ERP-BPMS deployment, while Case Company 4 introduced a performance-based incentive program offering bonuses of up to 12% of the base salary to meet operational targets. A survey of managers in both organizations (n = 14 and n = 18, respectively) attributed approximately 70% of performance gains to the new ERP-BPMS and IA oversight, with the remainder credited to concurrent organizational changes. The consistent pattern of improvements across metrics specifically targeted by the ERP-BPMS intervention strengthens the technology-driven impact.

In sum, the ERP-BPMS framework, reinforced by IA-led data validation, corresponded with meaningful enhancements in IQS, CPA, PMR, sourcing decisions, and IUR across four distinct critical infrastructure contexts. Case Company 4's significant SSI gains further attest to the value of integrated digital oversight for mission-critical utilities. While anomalies in IQS readings, the selective use of SSI, and potential short-term behavioral effects require careful interpretation, evidence of improved data quality, cross-departmental collaboration, and proactive maintenance strategies signals a durable shift toward data-centric operations.

This study examined how an integrated enterprise resource planning and business process management system (ERP-BPMS), reinforced by a dedicated information administrator (IA), can mitigate operational risks in critical infrastructure organizations. The investigation involved four anonymized companies representing diverse sectors: Case Company 1 (housing services), Case Company 2 (specialized construction), Case Company 3 (water technology), and Case Company 4 (energy utilities). This study sought to determine whether such integration could lead to significant improvements in *KPI* by consolidating personnel qualifications, maintenance logs, and cost-projection data within one unified digital platform. The discussion that follows interprets the findings, situates them within the existing literature, outlines theoretical contributions, draws practical managerial implications, acknowledges limitations, and suggests directions for future research. The findings reveal how integrated digital solutions can facilitate the transition from reactive to proactive operations in a critical infrastructure [33, 34].

Data Sources Note: Throughout the Discussion section, several supplemental percentage-based findings complement the primary metrics reported in the Results section. These supplemental findings are derived from three distinct sources: (1) qualitative interviews conducted with managers and technical personnel during the post-implementation phase; (2) internal organizational logs and documentation made available to researchers; and (3) secondary analyses performed on subsets of the primary data. Specifically, the reported reductions in diagnostic errors (66% in Case Company 1) and improvements in document retrieval accuracy (40% to 87% in Case Company 2) were extracted from the internal operational logs shared during IA-led interviews. The reductions in rework (10–25% in Case Company 2) and improvements in project timeline adherence (20% in Case Company 3) emerged from structured interviews with department managers and were subsequently validated against available project documentation. These supplemental metrics, which are not included in the primary results tables, provide valuable contextual evidence that supports and illustrates the broader impact of the ERP-BPMS intervention beyond the core metrics formally tracked across all four organizations.

The empirical results indicate that ERP-BPMS intervention, when supported by active IA oversight, produces statistically significant improvements across multiple operational metrics. For example, in Case Company 1, the integral qualification score (*IQS*) increased from 9.5 to 42.1, while diagnostic errors dropped by nearly 66%, according to internal operational logs. Qualitative feedback from technical managers suggests that this dramatic rise in *IQS* is partly attributable to the ratio-based formula – incorporating "+ 1" constants – and partly reflects a genuine recalibration of previously underreported staff competencies [19].

It is important to emphasize that the mathematical structure of the *IQS* formula inherently amplifies improvements when positive factors increase, whereas negative factors simultaneously decrease. The multiplicative relationship between the positive factors in the numerator and negative factors in the denominator, each with added "+ 1" constants, creates a compounding effect that magnifies even modest operational improvements. For instance, when a worker improves across multiple positive dimensions (e. g., experience, quality, risk awareness) while reducing negative aspects (e. g., rework, complaints), the formula produces a disproportionately large *IQS* value. This amplification effect, while methodologically sound to avoid zero denominators and capture multidimensional improvements, requires careful interpretation when evaluating the magnitude of the operational gains. Nevertheless, the consistent positive correlations between *IQS* improvements and supervisor assessments ($r \geq 0.70$) across multiple case companies confirm that these metrics reflect genuine operational advancements beyond mathematical artifacts.

Similarly, in Case Company 2, consolidating siloed scheduling, cost-projection, and resource-allocation data contributed to a reduction in rework between 10% and 25%, as reported during managerial interviews. For the smaller Case Company 3, which integrated sensor-driven analytics with traditional ERP data, adherence to project timelines improved by 20% based on project documentation analysis, and cost prediction accuracy (*CPA*) advanced from 0.70 to approximately 0.86. Lastly, Case Company 4 demonstrated a marked improvement in the system stability index (*SSI*), which increased from 1.04 to 1.31, suggesting fewer and briefer service outages following the centralization of maintenance records.

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A key element emerging from the cross-case analysis is IA's role. Across all four companies, monthly audits and real-time data reconciliations performed by the IA were instrumental in ensuring that the standardized metrics remained reliable. In larger settings, such as Case Company 4, one full-time IA oversaw the data governance of approximately 500 employees, while in smaller contexts such as Case Company 3, a part-time arrangement was sufficient. In Case Company 1, the IA conducted weekly data quality reviews that reduced diagnostic errors by 66%, as documented in internal quality reports, standardized maintenance terminology across departments, and hosted monthly cross-functional workshops to resolve data conflicts. Similarly, in Case Company 2, the IA implemented a metadata tagging system for project documentation that improved the retrieval accuracy from 40% to 87% according to system usage metrics and eliminated duplicate records. In every instance, active IA monitoring contributed to consistent improvements in the data accuracy. This consistency suggests that the reported performance gains are not merely a transient "honeymoon" effect, but also reflect an enduring shift toward a data-centric operational culture.

When comparing these findings with those of the existing literature, several points of convergence and extension become evident. Earlier studies have shown that ERP systems can streamline transactional data [9] and that BPMS solutions enhance workflow automation [16]. However, most of these studies have treated these technologies separately. In contrast, the present study indicated that the joint integration of ERP and BPMS with human oversight can yield compounded benefits. This observation aligns with ISO 31000, which advocates for ongoing risk identification, evaluation, and mitigation [20]. Embedding regular IA-led audits and real-time updates into daily operations effectively operationalized these guidelines and established a feedback loop for continuous risk management.

The results also resonate with insights from the technology acceptance model (TAM), wherein perceived usefulness and ease of use are crucial determinants of technology adoption [8]. In Cases 2 and 3, staff initially showed resistance to the new digital framework; once they observed tangible benefits, such as reduced rework and enhanced cost forecasting, their acceptance of the ERP-BPMS grew markedly. This behavioral change supports the idea that when employees perceive clear advantages such as fewer operational errors and more accurate maintenance scheduling, they are more likely to integrate these systems into their daily decision-making processes.

From a theoretical standpoint, this study makes several important contributions. First, it enriches BPM maturity theories by providing empirical evidence that integrating ERP and BPMS functionalities can move organizations from ad hoc process management to a more mature state of proactive risk governance [9, 14, 15]. These findings align with [13] research on public sector ERP implementation, where similar challenges in data governance and process standardization were identified as critical success factors for operational transformation. The consolidation of disparate data, ranging from personnel competencies to financial forecasts, within a unified platform exemplifies a structured trajectory toward higher BPM maturity. Second, by operationalizing ISO 31000 through monthly IA audits and multi-dimensional performance indicators, including *IQS*, *CPA*, *PMR*, and *SSI*, the study illustrates that risk management principles can be embedded as an iterative process rather than handled sporadically. Third, while the study did not formally test all TAM constructs, the observed increase in user acceptance provides indirect evidence that perceived usefulness driven by visible operational gains fosters the adoption of digital tools in high-stakes workflows.

This study offers several valuable insights. One clear implication is that adopting a unified ERP-BPMS platform reinforced by a dedicated IA role can significantly bolster the operational resilience. IA emerges as a linchpin, ensuring data quality, consistency, and continuity, as seen by the substantial reductions in discrepancies and errors.

For larger entities, a full-time IA managing a ratio of approximately one specialist per 500 employees may be effective, while smaller firms can likely replicate these benefits through part-time or shared IA roles. It is worth noting that the resource implications for the role of IAs vary significantly depending on organizational size. In larger entities such as Case Company 4, one full-time IA managed the data governance of approximately 500 employees with an annual position cost of about 85,000–95,000 USD (including overhead). In contrast, the smaller Case Company 3 effectively implemented IA functions at 0.3–0.4 FTE (approximately 12–16 hours weekly) with proportionally lower costs (30,000–40,000 USD annually). Notably, regardless of organizational size, the IA role demonstrated a clear return on investment: in Case Company 1, IA-led data audits reduced diagnostic errors by 66%, whereas in Case Company 2, they improved document retrieval accuracy from 40% to 87%. These improvements translated into measurable resource savings that significantly outweighed the costs of maintaining the role of IA. This suggests a strong economic case for this position, even in resource-constrained organizations. The cross-case analysis further suggests that a staged implementation, beginning with a pilot phase for core modules, can unveil data inconsistencies early and inform tailored training programmes. Managers in sectors such as construction and water technology, where cost accuracy and project timelines are critical, may benefit substantially from such phased rollout. Integrating real-time sensor data with conventional ERP inputs, as demonstrated by Case Company 3, refines predictive maintenance and resource allocation strategies, thereby minimizing unplanned downtime and reactive expenditures.

Despite the promising outcomes, this study has several limitations that affect the broader applicability of its findings. The six- to eight-month observation window is relatively brief compared to the multi-year project cycles typical of large-scale energy or construction. It remains uncertain whether the initial improvements, possibly heightened by a temporary surge in diligence, will be sustained in the long term. It is particularly important to note that the six- to eight-month observation window, while yielding statistically significant results, may have captured novelty effects or the Hawthorne effect, where heightened attention to processes temporarily improved metrics. Confirming the persistence of the observed improvements would require an extended follow-up or a controlled design that could establish whether the benefits of ERP-BPMS and IA oversight endure beyond the heightened awareness phase typical of pilot projects. Follow-up measurements at 18–24 months are recommended to validate the stability of the results. Additionally, the quasi-experimental design, lacking a randomized control group, complicates the definitive attribution of performance gains to the ERP-BPMS and IA alone; confounding factors such as organizational restructuring or temporary managerial incentives may also have played a role. The use of ratio-based metrics, notably *IQS*, although methodologically justifiable for avoiding zero denominators, can numerically inflate improvements, thus necessitating caution when comparing across different operational contexts. Finally, while the IA role proved instrumental here, the cost implications and scalability for organizations with tighter budgets or more limited workforces remain open questions.

Future research could address these limitations by employing longer-term, controlled designs that span multiple project cycles, particularly in high-stakes sectors, such as specialized construction or large-scale energy. Implementing staggered ERP-BPMS rollouts across comparable organizational units may isolate the direct effects of digital intervention and reinforce causal inferences. Additionally, integrating advanced analytics, such as AI-driven predictive maintenance, digital twins, or anomaly detection algorithms, into the ERP-BPMS architecture represents a logical next step for further enhancing the operational efficiency [35]. In particular, integration with BIM data mining [36] and digital twin technologies [37, 38], which could offer more sophisticated predictive capabilities and visualization of complex system interdependencies. Machine learning techniques, as demonstrated by [5], can further enhance the identification and management of systemic risks in infrastructure projects, complementing the integrated ERP-BPMS approach with predictive analytics capabilities. The repercussions of such integrations on IA workloads and requisite skill sets warrant a systematic investigation. Another promising line of inquiry involves the cost–benefit analysis of the IA function, clarifying whether certain staffing ratios or professional backgrounds optimize data governance and risk mitigation in various industrial settings. Furthermore, broadening the scope to other critical infrastructure sectors, such as transportation or healthcare, could elucidate how differing regulatory demands and cultural factors shape the success of integrated ERP-BPMS solutions. The formal application of TAM constructs or related user acceptance models might also shed quantitative light on how perceived usefulness evolves once employees recognize concrete gains, such as minimized rework and more accurate forecasting [8].

The empirical evidence presented here shows that a combined ERP-BPMS environment and IA oversight can significantly reduce operational vulnerabilities in diverse critical infrastructure organizations. Improvements in key metrics, including *IQS*, *CPA*, *PMR*, *IUR*, and *SSI*, highlight the potential of this integrated approach to both streamline day-to-day processes and foster a culture of continuous risk management. By relating these findings to ISO 31000 guidelines, BPM maturity models, and partial alignments with TAM, this study contributes theoretically, while offering practical pathways for digital transformation in high-stakes industries. Although the short observation window and quasi-experimental design caution against broad generalizations, the consistency of results across the four distinct contexts underscores the promise of combining technical integration with structured human oversight.

3.6. Limitations of the study

Several limitations should be acknowledged when interpreting and applying the findings of this research. The six- to eight-month observation window is relatively brief compared to multi-year project cycles typical in large-scale energy or construction sectors, making it difficult to fully assess the long-term sustainability of the observed improvements. The study may have captured novelty effects or the Hawthorne effect, where heightened attention to processes temporarily improved metrics rather than reflecting lasting operational changes. Confirming the persistence of these improvements would require extended follow-up measurements at 18–24 months post-implementation.

Additionally, the quasi-experimental design without a randomized control group complicates definitive attribution of performance gains to the ERP-BPMS and IA interventions alone. Confounding factors such as concurrent organizational restructuring (particularly in Case Companies 1 and 4) and temporary managerial incentives may have influenced the results. The study's ratio-based metrics, notably *IQS*, though methodologically justified to avoid zero denominators, can numerically amplify improvements, necessitating caution when comparing across different operational contexts.

While the IA role proved instrumental in all four cases, questions remain about cost implications and scalability for organizations with tighter budgets or more limited workforces. The demonstrated benefits may not translate equally to all critical infrastructure contexts, particularly those with significantly different regulatory environments or organizational cultures. These limitations should be considered carefully when attempting to generalize or apply the framework in different settings.

These limitations highlight the need for additional research to strengthen and validate our findings. Future researches should address these constraints by extending observation periods to 18–24 months, incorporating randomized control-group comparisons where feasible, and accounting for confounding organizational factors through more rigorous statistical controls.

To advance this line of inquiry, researchers should also explore integration with emerging technologies such as AI-driven anomaly detection and digital twin simulations [35], which could refine predictive analytics capabilities and better account for the recalibration effects observed in our metrics. Such technological enhancements would provide more granular insights into operational risk patterns while controlling for the mathematical amplification effects noted in our *IQS* measurements.

Despite these limitations, our study makes valuable contributions by validating a robust ERP-BPMS risk-mitigation framework that bridges theoretical insights with practical, replicable interventions. The framework provides project managers with adaptive, evidence-based approaches to operational risk management in critical infrastructure contexts. In this way, this research advances the broader mission of integrating information systems management with project management methodologies [8], while establishing a foundation for future empirical investigations of digital transformation in high-stakes infrastructural environments.

4. Conclusions

This multi-case study demonstrates that combining an enterprise resource planning and business process management system (ERP-BPMS) with a dedicated information administrator (IA) can substantially mitigate operational risks in critical infrastructure settings. Drawing on data from four anonymized organizations – Case Company 1 (housing services), Case Company 2 (specialized construction), Case Company 3 (water technology), and Case Company 4 (energy utilities) – it is possible to observe notable gains in key performance indicators during the six- to eight-month post-implementation period. For example, in Case Company 1, the integral qualification score (*IQS*) rose from 9.5 to 42.1, while the cost prediction accuracy surpassed 0.85 across all firms. Preventive maintenance ratios increased by 15–20 percentage points and the information utilization rate increased by 20–30 points. Case Company 4's system stability index (*SSI*) advanced from 1.04 to 1.31, underscoring how integrated data streams and automated workflows can reduce downtime [6, 7].

These empirical outcomes directly address both the research questions. First, the significant improvements in error reduction, forecasting precision, and preventive maintenance confirm Hypothesis 1, indicating that a holistic ERP-BPMS framework systematically lowers operational vulnerabilities in high-stake domains. Second, the role of IA emerged as pivotal in amplifying these benefits, offering structured human oversight through monthly audits and cross-departmental coordination, thereby resolving Research Question 2 and validating Hypothesis 2. This synergy between technological integration and data governance aligns with ISO 31000 principles by providing a coherent structure for proactive risk management [1, 20]. This approach is particularly valuable in contexts that require smart project management systems to coordinate complex operations [39, 40].

Theoretically, this study enriches discussions on BPM maturity by demonstrating how ERP functionalities and IA-led oversight can be operationalized to elevate both process efficiency and resilience [9]. In practice, it offers a scalable roadmap for diverse critical infrastructure environments. Larger entities may adopt full-time IAs to maintain rigorous data governance, whereas smaller organizations, such as Case Company 3, might implement part-time or shared IA models without compromising key performance gains. Although the consistency of the results indicates genuine improvements, the short observation window (six–eight months) and quasi-experimental design preclude definitive claims on long-term sustainability, and the Hawthorne effect cannot be fully dismissed [32].

Conflict of interest

The authors declare that they have no conflict of interest regarding this research, including financial, personal, authorship, or other interests that could have influenced the research and its results presented in this article.

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Data availability

Data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that no artificial intelligence technologies were used in the creation of the presented work.

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