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Economic Viability of Decision Support Systems for Emergency Risk Reduction in Chemical Industries

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ABSTRACT: This study assesses the economic feasibility of implementing a Decision Support System (DSS) in chemical process industries for emergency management and risk reduction. Recognizing the financial stakes involved in industrial incidents, the research evaluates the costs and returns associated with DSS adoption through a structured cost-benefit analysis. The methodology incorporates capital expenditure (CAPEX), operating expenditure (OPEX), avoided incident losses, and insurance premium reductions. Using data modeling and sensitivity analysis, the study calculates net financial benefits and payback periods under various scenarios, ranging from conservative to optimistic projections. Key findings reveal that the DSS investment of USD 450,000, with an annual OPEX of USD 85,000, yields annual economic benefits of USD 290,000 through incident cost avoidance and insurance savings. This translates to a net benefit of USD 205,000 annually and a payback period of approximately 2.2 years. Even under conservative assumptions, the system demonstrates economic viability, confirming its potential to deliver substantial returns beyond its safety functions. The conclusion affirms that DSS integration not only enhances operational safety but also provides compelling financial justification. It encourages broader adoption in high-risk industrial sectors and advocates for future research that integrates intangible benefits and long-term impacts into economic evaluations.

Keywords: Decision Support System, Cost-Benefit Analysis, Chemical Safety, ROI, Emergency Management, Industrial Risk, Economic Evaluation

INTRODUCTION

Chemical process industries (CPI) operate within environments that inherently present significant risks, primarily due to the hazardous nature of substances involved in production, processing, and storage. Among the most frequent and high-consequence threats are chemical leaks, explosions, fires, and critical equipment failures. These incidents, whether minor or catastrophic, pose threats not only to the safety of personnel and surrounding communities but also to environmental integrity and operational continuity. Events such as the Bhopal disaster underscore the severe ramifications of inadequate risk control and emergency preparedness (Cui & Wu, 2016).

Given the complexity and potential severity of these industrial hazards, there is an urgent demand for robust, real-time solutions that enhance decision-making and response efficiency. Decision Support Systems (DSS) have emerged as a transformative tool in this context, enabling data-driven support for managing emergencies more effectively(Baruffaldi et al., 2019; Cánovas-Segura et al., 2023; Cui et al., 2025). DSS integrate diverse technological capabilities including real-time monitoring, historical data analysis, modeling, and simulation to guide operators during high-stress situations (Symeonaki et al., 2020). The dynamic nature of DSS allows it to assimilate equipment conditions, chemical inventories, and real-time risk indicators to deliver prompt and accurate recommendations. These systems can also identify patterns from past events, enabling the prediction of potential failures and the preparation of mitigation strategies (Lin et al., 2018).

Modern DSS implementations are driven by advanced technologies such as artificial intelligence (AI), cloud-based platforms, and Internet of Things (IoT) infrastructures. AI facilitates predictive analytics that detect anomalies and forecast system failures, while IoT networks provide seamless data transmission from sensors embedded in process equipment. These components collectively contribute to improved visualization, decision-making accuracy, and risk mitigation. Visualization tools, in particular, allow operators and safety personnel to comprehend complex datasets, enabling faster interpretation and appropriate response measures (Bach et al., 2023; Çınar et al., 2020).

The efficacy of DSS has been validated through various case studies, particularly in high-risk sectors such as petrochemical manufacturing. For example, DSS implementations in hazard-prone facilities have led to improved regulatory compliance and decreased operational downtime. The systems proved instrumental in identifying latent risks associated with chemical processing and facilitated the timely execution of preventive actions (Cui & Wu, 2016). Furthermore, when integrated with predictive maintenance modules, DSS have been shown to deliver dual advantages minimizing safety incidents and enhancing production reliability (Lin et al., 2018).

While the technical advantages of DSS are well documented, the cost-effectiveness of such safety interventions has attracted increasing academic and industrial attention. Quantitative evaluations utilizing cost-benefit analyses and Return on Investment (ROI) models indicate that DSS can produce significant long-term economic gains despite high initial costs (Guimapi et al., 2020). These savings are attributed to reduced liabilities, fewer unplanned downtimes, and improved operational efficiency. Moreover, the presence of DSS contributes to higher productivity levels, reinforcing its value as a financially sound investment (Rahman et al., 2021).

The implementation of DSS in chemical processing industries is further guided by well-established frameworks and safety standards. Regulatory guidelines such as OSHA's Process Safety Management (PSM), ISO 45001, and other international safety norms establish a foundation for integrating technology within structured risk management strategies. These standards emphasize proactive hazard identification, risk mitigation, and continual improvement, aligning closely with the capabilities offered by DSS (Cui & Wu, 2016).

In light of the multifaceted role of DSS in promoting safety and operational continuity, this study focuses on its economic justification in chemical plant environments. Despite growing interest, there remains a research gap in the comprehensive financial evaluation of DSS. Specifically, it is unclear whether the economic benefits derived from avoided incident costs and insurance reductions sufficiently outweigh the upfront and ongoing expenses. This study seeks to fill this gap by providing an empirical cost-benefit analysis of DSS implementation, estimating capital and operational expenditures against quantifiable financial gains.

The objective of this research is to demonstrate the economic viability of DSS in high-risk industrial operations. By quantifying both the investment requirements and the projected financial returns, this work aims to support strategic decision-making among safety managers and financial stakeholders. The novelty of this study lies in integrating economic metrics with real-time safety technology evaluation, offering a practical framework for industrial investment analysis in process safety management.

METHOD

Overview

This chapter outlines the methodological approach used to evaluate the economic feasibility of implementing a Decision Support System (DSS) in chemical process industries. The methodology integrates established economic evaluation techniques to quantify the financial impacts of DSS deployment, focusing on capital and operational expenditures, projected financial benefits, and investment viability.

Evaluation Framework

The economic evaluation relies on three primary financial tools: Cost-Benefit Analysis (CBA), Return on Investment (ROI), and Payback Period calculation. CBA is employed to compare total DSS-related expenditures with anticipated economic gains, such as avoided losses and insurance savings (Nwulu et al., 2024). ROI is used to determine the percentage return derived from the DSS investment by comparing net benefits to total investment costs. Meanwhile, Payback Period analysis calculates the time required to recover the initial investment from annual net savings, serving as a practical indicator of investment performance (Shafiee, 2024).

DSS Investment Components

Capital Expenditure (CAPEX)

CAPEX refers to the upfront cost associated with the acquisition, development, and installation of the DSS. This includes investments in sensors, servers, software platforms, and system integration services. CAPEX estimation is informed by historical cost data, expert assessments, and standard pricing models relevant to safety technologies (Blouin, 2023). For the purpose of this analysis, a total CAPEX of USD 450,000 was used, encompassing all components necessary for initial DSS deployment.

Operating Expenditure (OPEX)

OPEX consists of recurring annual costs related to system operation and maintenance. This includes licensing fees, software updates, hardware servicing, staff training, and other support services. OPEX estimation draws on maintenance schedules, labor forecasts, and historical expenditure patterns in similar industrial applications (Shafiee & Animah, 2017). The study assumes an annual OPEX of USD 85,000.

Benefit Components

Avoided Incident Losses

Avoided losses represent the projected reduction in economic damages resulting from the DSS's improved detection and emergency response capabilities. These losses typically include costs related to equipment downtime, environmental fines, personnel injuries, and product losses. Based on industry benchmarks and historical incident costs, the avoided loss was estimated at USD 260,000 per year.

Insurance Benefits

DSS adoption is also expected to reduce insurance premiums or increase risk ratings due to enhanced safety performance. The annual financial gain from such adjustments was conservatively estimated at USD 30,000.

Economic Metrics and Formulas

Net Benefit

Net Benefit = (Avoided Loss + Insurance Benefit) – OPEX = (260,000 + 30,000) − 85,000 = USD 205,000 per year

Payback Period

Payback Period = CAPEX / Net Benefit = 450,000 / 205,000 ≈ 2.2 years

Return on Investment (ROI)

ROI = (Net Benefit / CAPEX) × 100 = (205,000 / 450,000) × 100 ≈ 45.6%

These metrics provide a comprehensive view of the financial performance of DSS implementation, enabling stakeholders to make informed decisions.

Sensitivity Analysis

To accommodate uncertainty and variability in cost and benefit estimates, a sensitivity analysis was conducted. This analysis examined three scenarios:

- Conservative: Avoided loss = USD 200,000; Insurance benefit = USD 20,000; Net Benefit = USD 135,000
- Base case: Avoided loss = USD 260,000; Insurance benefit = USD 30,000; Net Benefit = USD 205,000
- Optimistic: Avoided loss = USD 300,000; Insurance benefit = USD 50,000; Net Benefit = USD 265,000

Each scenario was evaluated using the same financial formulas to assess changes in ROI and payback periods under varying economic conditions.

Limitations

While the methodology incorporates widely accepted economic tools, the study is limited by its reliance on estimated values. Future work should seek to validate these findings using empirical operational data and real-world DSS implementations in chemical industries.

RESULT AND DISCUSSION

Investment Breakdown

The capital investment required for Decision Support System (DSS) implementation varies across industries and system complexities. In chemical process industries, CAPEX for DSS is typically within the range of USD 100,000 to 500,000 for smaller facilities, while more complex implementations in larger or high-risk operations may exceed USD 1 million (Mittas & Mitropoulos, 2022). This investment includes procurement of sensors, servers, software licenses, and integration services. In this study, the evaluated CAPEX was USD 450,000.

Recurring Operational Expenditure (OPEX) consists of costs related to licensing, maintenance, and personnel training. Licensing fees can range from USD 20,000 to 200,000 annually depending on the scale of deployment. Maintenance typically accounts for 15–20% of software costs, while training may cost USD 5,000–20,000 annually (Mendoza, 2016). For the evaluated DSS, annual OPEX was estimated at USD 85,000.

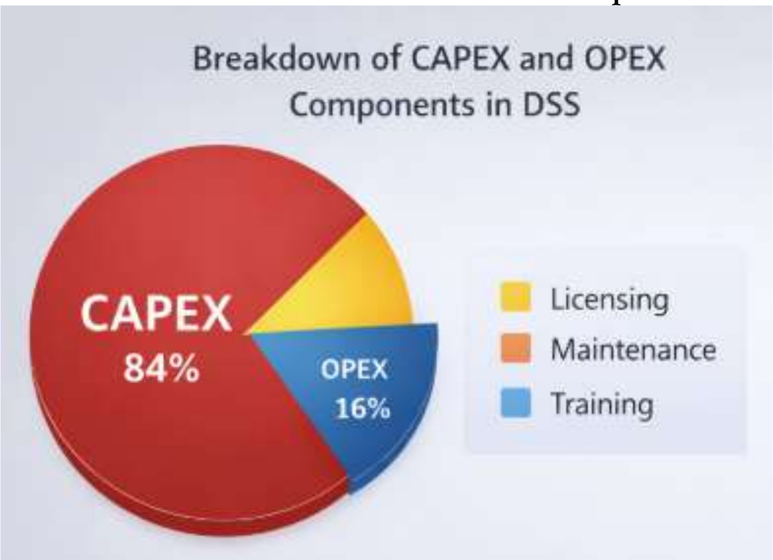
Licensing and training are essential for ensuring effective DSS utilization. Insufficient training can lead to underutilization or operational errors, which in turn can affect overall system performance and negate economic gains (Mittas & Mitropoulos, 2022). Licensing, while necessary for software access and updates, contributes to consistent long-term OPEX.

Sectoral differences also shape DSS investment profiles. For instance, oil and gas industries require high-end predictive and safety analytics, often exceeding USD 1 million in CAPEX. Conversely, manufacturing sectors may operate with simpler DSS configurations under USD 300,000, driven by lower risk thresholds and regulatory demands (Mittas & Mitropoulos, 2022).

Table 1. Investment Summary for DSS Implementation

Investment Category	Cost Range (USD)	Cost in Study (USD)
CAPEX (System Setup)	100,000 – >1,000,000	450,000
Licensing (Annual OPEX)	20,000 – 200,000	Included
Maintenance (per year)	15–20% of software cost	Included
Training (per year)	5,000 – 20,000	Included
Total Annual OPEX	Varies by configuration	85,000

Figure 1. Breakdown of CAPEX and OPEX Components in DSS



A pie chart representing CAPEX vs. OPEX and sub-categories (licensing, training, maintenance)

Benefits

Chemical plant incidents result in substantial financial losses, often ranging from several million to over USD 100 million per incident due to environmental damage, lawsuits, and equipment downtime (Linnerooth-Bayer et al., 2018). The implementation of DSS helps mitigate these risks by improving monitoring and proactive decision-making.

Avoided losses are calculated through comparative incident data and modeling techniques that estimate the economic impacts of incidents that were prevented or mitigated. In this study, annual avoided losses due to DSS integration were estimated at USD 260,000 based on downtime reductions and improved incident response (Linnerooth-Bayer et al., 2018).

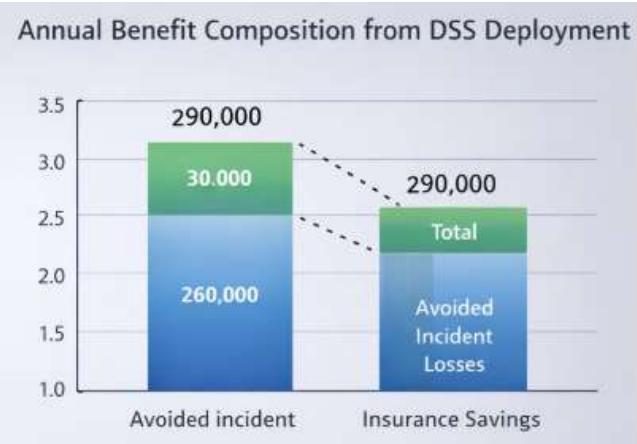
Additionally, DSS contributes to insurance premium reductions. Insurers recognize reduced operational risk through DSS integration and may offer 10–30% lower premiums following verified system use. This study conservatively estimated USD 30,000/year in insurance savings (Maluleka & Chummun, 2024).

Benchmarks for evaluating such cost savings include incident rate reductions, comparative claims data, and productivity improvements, affirming the value of proactive safety investments (Linnerooth-Bayer et al., 2018).

Table 2. Economic Benefits of DSS Implementation

Benefit Component	Estimated Annual Value (USD)
Avoided Incident Losses	260,000
Insurance Premium Reduction	30,000
Total Annual Benefit	290,000

Figure 2. Annual Benefit Composition from DSS Deployment



A stacked bar chart showing avoided losses and insurance savings

ROI and Payback

Return on Investment (ROI) and payback period are critical indicators for assessing technology investment performance. ROI is calculated by comparing annual net benefits to CAPEX, while the payback period measures how quickly the investment is recovered through savings (Mittas & Mitropoulos, 2022).

In this analysis:

- ROI = (USD 205,000 / USD 450,000) × 100 ≈ 45.6%

- Payback period = USD 450,000 / USD 205,000 ≈ 2.2 years

High-risk industries often require shorter payback windows, typically 1–3 years, to justify substantial CAPEX and mitigate investment uncertainty (Maluleka & Chummun, 2024). Sensitivity to economic assumptions such as operating costs, risk reduction outcomes, and discount rates makes ROI and payback analysis vital to informed decision-making (Mendoza, 2016).

Empirical case studies further validate DSS benefits. In one example, a chemical plant reported a 25% reduction in incident-related costs, leading to a sub-2-year payback period. Some firms noted ROI exceeding 300% from operational savings and compliance improvements (Maluleka & Chummun, 2024).

Table 3. ROI and Payback Period Summary

Metric	Value
Net Benefit	USD 205,000/year
ROI	45.6%
Payback Period	2.2 years

Sensitivity Analysis

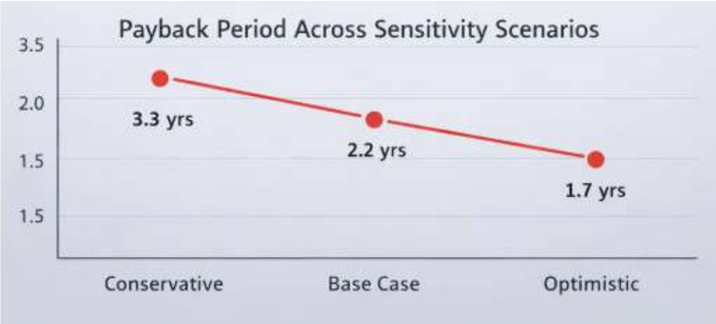
Scenario-based modeling techniques are widely employed to assess investment robustness under conservative, base, and optimistic financial assumptions (Mendoza, 2016). This study examined three scenarios:

- **Base Case**: Avoided loss USD 260,000; insurance benefit USD 30,000 → net benefit USD 205,000
- **Conservative**: Avoided loss USD 200,000; insurance benefit USD 20,000 → net benefit USD 135,000; payback = 3.3 years
- **Optimistic**: Avoided loss USD 300,000; insurance benefit USD 50,000 → net benefit USD 265,000; payback = 1.7 years

Table 4. Sensitivity Analysis of DSS Financial Outcomes

Scenario	Avoided Loss (USD)	Insurance Benefit (USD)	Net Benefit (USD/year)	Payback (years)
Conservative	200,000	20,000	135,000	3.3
Base Case	260,000	30,000	205,000	2.2
Optimistic	300,000	50,000	265,000	1.7

Figure 3. Payback Period Across Sensitivity Scenarios



A line graph illustrating the payback period progression under different benefit assumptions

The economic evaluation of Decision Support Systems (DSS) in chemical industries demonstrates significant financial viability. A key driver of the favorable return on investment (ROI) is the reduction in accident-related costs. Organizations deploying safety technologies such as DSS report fewer incidents, leading to diminished liabilities, including legal penalties, insurance claims, and regulatory fines (Kim et al., 2022). In this context, ROI is closely linked to safety performance outcomes. Enhanced compliance with regulatory standards further strengthens the economic case for DSS, as firms avoid costly violations and position themselves more favorably in audits and industry assessments (Krasuski et al., 2022).

Another critical contributor to ROI is improved operational efficiency. DSS implementations often streamline workflows and reduce unplanned downtime, resulting in a more productive and responsive operational environment (Sano & Koshiba, 2024). These improvements not only translate into immediate economic benefits but also support long-term strategic goals such as sustainability and competitiveness. Over time, the integration of such safety technologies fosters a cultural shift within organizations, reinforcing a safety-oriented mindset and accountability, which further amplifies both economic and operational returns (Adenuga et al., 2020).

Despite these advantages, uncertainties in financial inputs remain a substantial concern when evaluating DSS investments. Market fluctuations, unforeseen maintenance costs, and variable operational expenses can significantly influence cash flow forecasts and complicate ROI assessments. Furthermore, quantifying the benefits of risk reduction technologies poses challenges, especially in the absence of consistent, empirical data linking safety technology adoption to measurable financial outcomes (Gurung et al., 2017). Decision-makers must contend with limited visibility into how such investments affect incident rates or efficiency metrics, often prompting a conservative approach to capital allocation.

Cost-benefit analyses of safety systems are also subject to methodological limitations. One prominent issue is the underrepresentation of intangible benefits such as improved employee morale, reputational gains, and stakeholder trust. While these factors can yield substantial indirect returns, they are difficult to monetize and are often excluded from conventional models, potentially leading to undervaluation of DSS investments (Fasoro & Ajewole, 2019). Additionally, many evaluations depend on historical incident data, which may not accurately reflect future conditions due to changes in technology, regulation, or industrial practices (Archetti et al., 2017).

Such retrospective approaches can obscure the forward-looking value of DSS, especially in rapidly evolving operational contexts.

The time lag between investment and observable benefit adds further complexity. Safety investments may take several years to demonstrate full economic impact, which complicates the justification process for capital-intensive technologies. Furthermore, stakeholder perspectives on the value of safety vary; some prioritize short-term financial returns, while others advocate for long-term resilience, leading to inconsistent assessments and decision-making outcomes (Gurung et al., 2017).

To address these limitations, future research should prioritize the development of integrated models that capture both tangible and intangible benefits of safety technologies. Incorporating qualitative metrics into economic evaluations can provide a more comprehensive understanding of investment impacts (Sano & Koshiba, 2024). Longitudinal studies assessing the enduring value of DSS over time would also enhance evidence-based decision-making, especially in high-risk sectors. Moreover, the application of advanced analytics and machine learning to incident prediction and financial forecasting holds promise for improving the accuracy of cost-benefit analyses (Sarkar, 2016).

Collaborative research between academic institutions and industrial stakeholders could also lead to the standardization of evaluation practices. Creating universally accepted frameworks and benchmarks would facilitate consistent, transparent assessment of DSS investments, supporting better alignment between safety performance and financial objectives (Sano & Koshiba, 2024).

CONCLUSION

This study evaluated the economic viability of implementing a Decision Support System (DSS) within the chemical process industry, integrating both cost and benefit metrics to determine its return on investment. The findings underscore that DSS not only enhances emergency response capabilities but also yields measurable financial advantages.

The analysis revealed that the initial capital investment of USD 450,000 and recurring annual operating expenses of USD 85,000 are effectively offset by annual savings from avoided incident losses and insurance premium reductions, estimated at USD 260,000 and USD 30,000 respectively. This translates into a net benefit of USD 205,000 per year, achieving a payback period of approximately 2.2 years. Sensitivity analyses further confirmed that even under conservative financial scenarios, DSS investments remain economically justifiable, with payback periods extending no further than 3.3 years.

These results demonstrate that DSS provides more than compliance or safety enhancement it offers strategic economic value. It helps reduce liabilities, prevent operational disruptions, and improve regulatory compliance, all of which contribute to a safer and more financially resilient organization. Moreover, DSS fosters a culture of safety and accountability, reinforcing long-term operational integrity and performance.

Despite some limitations in data assumptions and long-term forecasting, the evidence strongly supports broader adoption of DSS technologies in high-risk industrial environments. Organizations considering such investments are advised to evaluate both direct and indirect benefits, including intangible gains such as employee morale, stakeholder confidence, and corporate reputation.

In conclusion, DSS implementation represents a prudent and financially sound decision for chemical processing facilities. Future research should aim to further refine economic models by incorporating empirical data and expanding the scope of evaluation to include both quantitative and qualitative impacts. Establishing standardized evaluation frameworks across industries will also facilitate informed and consistent decision-making, advancing the adoption of safety technologies globally.

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