Journal of Applied Research and Technology

www.jart.icat.unam.mx

Instituto de Ciencias Aplicadas y Tecnología

Journal of Applied Research and Technology 23 (2025) 489-503

Original

Simultaneous Optimization of Investment in Technology Implementation and Regulatory Compliance: A Supply Chain Decision Model

M. Monsreal[1] • S. Ozkul[2] • R.B. Carmona-Benítez*[3,4] • O. Cruz-Mejia[5]

[1]Texas A&M Transportation Institute, Bryan, Texas, USA. ORCID: 0000-0001-9856-8259
[2]Supply Chain Innovation Lab, University of South Florida, Tampa, Florida, USA. ORCID: 0000-0003-1509-8795
[3]Universidad Anáhuac México, Facultad de Economía y Negocios, Huixquilucan, Estado de México, Mexico. ORCID: 0000-0002-8369-2748
[4]Universidad Nacional Autónoma de México, Facultad de Ingeniería, Ciudad de México, México. ORCID:0000-0002-8369-2748
[5]FES Aragón, Universidad Nacional Autónoma de México, Nezahualcóyotl, Estado de México, México. ORCID: 0000-0001-7362-6408

Received 05 26 2025; accepted 31 07 2025
Available 31 10 2025

Abstract: A mathematical optimization model is proposed for strategic decision-making in supply chain management (SCM). The proposed model simultaneously optimizes investments to comply with government regulations and investments in technology to improve efficiency across three performance dimensions: ordering, just-in-time (JIT), and operating efficiency. Real company data is used to test the model. This data comes from a German company. The behavior of the proposed model is analyzed by solving four scenarios under different investment strategies. Results reveal counterintuitive findings, for example, JIT efficiency does not necessarily increase when technology investment increases; in comparison compliance with government regulations can improve companies' operational efficiencies. These results demonstrate the sensitivity of companies' operations to the allocation of technology investment and highlight the importance of simultaneously optimizing investments in government regulations compliance, and in the

*Corresponding author.
E-mail address: *rafael.carmona@anahuac.mx (R.B. Carmona-Benitez).
Peer Review under the responsibility of Universidad Nacional Autónoma de México.

implementation of new technology. The optimization model informs the decision-making process that companies follow when investing in new technology while ensuring compliance with government regulations. Therefore, the model offers practical insights and utility for both private companies and government policymakers.

Keywords: **Supply chain management, supply chain optimization, technology investment, technology adoption, government regulations, regulatory compliance.**

1. Introduction

In supply chain management (SCM), the development and application of new technologies play a critical role in enhancing supply chain (SC) efficiency and reliability. Technology enables SC managers to make decisions across different time horizons–strategic decisions (i.e., facility locations), operational decisions (i.e., inventory management) and tactical decisions (i.e., fleet assignment)–to maximize benefits and minimize costs.

The effects of investing in compliance with government regulation and in technology in SCM are an important area of research, because companies must comply with government regulations while maximizing operational efficiency.

For example, manufacturers invest in technology, such as green technology, to minimize their environmental impact, often constrained by government regulations that aim to encourage sustainability (Ma et al., 2021; Liu et. al., 2021; Li et. al., 2022).

Thus, companies must consider the impacts of investing in compliance with government regulations and in technology in SCM because these factors affect operational efficiency, long-term competitiveness, and extend the return on investment capital. Despite the importance of these factors, there is a gap in the SCM literature regarding optimization models that simultaneously optimize investments in technology and investments in government regulation compliance in SC systems.

Therefore, balancing investments in compliance with government regulations and investments in technology is critical for SC companies to improve their operations and competitiveness (Charoenwong et al., 2024; Khoury et al., 2024; Ibiyeye, et al., 2024). This paper addresses this optimization problem by proposing a new model that simultaneously optimizes both investment variables, providing a new approach to decision-making in SCM.

In SC, investments in technology aim to improve decision-making, reduce operational times, minimize costs, and increase SC responsiveness. However, these advantages are limited by compliance with government regulations, which impose requirements related to product traceability, safety standards, and other factors that directly affect SC operations (Ezeigweneme et al. 2024). Failure to abide to these regulations leads to potential disruptions due to government inverventions and potential fines and penalties, which could affect the effectiveness of the entire SC and reduce its overall efficiency (Brehm & Hamilton, 1996; Shimshack & Ward, 2008; Gray & Shadbegian, 2021). Thus, companies must strategically invest in new technologies to ensure optimal performance (i.e., maximize efficiency and competitiveness) while assuring compliance with government regulations to avoid penalties and disruptions (Gray & Shadbegian, 2021). One example is the integration of data-driven marketing and blockchain technology to enhance transparency and help meet sustainability standards (Li et. al., 2022; Tuladhar et al., 2024; Wang et al., 2022); another example is the Food Safety Modernization Act (FSMA) 204 which is a regulation that requires companies to trace their products through SCs promoting the implementation of new technologies (Selvaraj, 2025). Hence, it is possible to conclude that governments influence supply chain decisions by issuing regulations to ensure sustainability while sometimes offering subsidies to achieve this goal; therefore, governments play a crucial role in SCM and in companies technology investments (Liu et al., 2021; Dubey et al., 2023; Nadirsyah & Mulyany, 2024). Therefore, studying the optimization of investments in compliance with government regulations and in technology is important for ensuring SC sustainability.

This paper addresses these gaps by proposing a new mathematical model that simultaneously optimizes both: the investments to comply with government regulations and the investments in technology, providing new information and guidance to related decision-making in SCM. The proposed model is the main contribution of the paper to the theory of SCM and builds upon the one developed by Monsreal et al. (2019), which also optimizes investments in compliance with government regulations and in technology, measured in monetary terms and referred to as investment levels. However, Monsreal et al. (2019) model optimizes only one variable at a time, which does not address some scenarios where multiple factors evolve simultaneously in SCs. As a result, that previous model can lead to suboptimal solutions when dealing with parallel dynamics arising from the interaction of multiple variables. To overcome this limitation, the optimization model proposed in this paper simultaneously optimizes investments in compliance with government regulations and in technology, considering the effects of both factors. Hence, the proposed optimization model is closer to the reality of a multifactorial decision-making process, than the previous model, allowing firms to make better decisions and apply more reliable SCM strategies.

This paper is organized as follows: Section 2 presents a literature review of gaps, technology investment models, and the role of government regulations in SCM. Section 3 introduces a mathematical optimization model that calculates the optimal levels of investment in compliance with government regulations and in technology in SCM. Section 4 presents a case study on end-to-end SC visibility using Auto-ID technologies, followed by an analysis of the results. Finally, the conclusions and directions for future research are provided.

2. Literature Review

2.1. Gap in Optimization of Technology and Regulatory Investments

Few studies have optimized technology investment decisions in SCM, as most rely on non-optimal approaches such as cost-benefit analysis, net present value (NPV), or feasibility studies. As explained in Section 1, this paper fills that gap by developing an optimization model that simultaneously calculates optimal investments in technology and in compliance with government regulations. Monsreal et al. (2019) emphasize the significance of these two variables through an international survey that examines investment decisions and economic development. This paper extends Monsreal et al. (2019) by incorporating optimization techniques to support strategic decision-making.

2.2. Technology Investment Decision Models in SCM

In SCM, technology investment decisions have traditionally relied on basic valuation methods. However, some studies have incorporated more advanced techniques such as Monte Carlo simulations (Doerr et al., 2006), real options analysis (You et al., 2012; Zandi & Tavana, 2011), and stochastic models (Kauffman et al., 2015). Despite these advances, the integration of regulatory compliance as a variable remains limited.

Some studies focus solely on financial optimization. For example, Perold (1984) and Konno and Yamazaki (1991) propose optimization methods for portfolio management; however, they are limited to financial markets and do not incorporate supply chain dimensions or regulatory constraints.

2.3. Strategic Technology Adoption in SCM

Technology adoption is widely recognized as a key driver of supply chain efficiency. IT systems enhance network visibility (Ghiassi & Spera, 2003), collaboration (Rai et al., 2007), and business efficiency (Gunasekaran & Ngai, 2004). However, adoption challenges persist due to cost-sharing concerns (Gaukler et al., 2007), unclear ROI (Heese, 2007), and slow diffusion (Atkin et al., 2017). Traceability technologies offer benefits for efficiency and compliance (Li et al., 2023), though interconnectivity issues complicate adoption.

Recent innovations include RFID (Sarac et al., 2010; Raza, 2022), Industry 4.0 (Hofmann & Rüsch, 2017; Kocatepe et al., 2020), smart manufacturing (Chiang et al., 2024; Lee et al., 2024; Huang et al., 2024), and supply planning in smart factories (Won & Park, 2020; Soori et al., 2023). Blaettchen et al. (2024) propose an optimization model to identify early adopters of traceability technologies, though they do not address regulatory impacts.

2.4. Role of Government Regulations in SCM

Compliance with government regulations plays a critical role in shaping SCM strategies. Regulatory environments influence cost structures, technology adoption, and market dynamics (Menon & Lee, 2000). Economic instruments like carbon pricing and subsidies encourage sustainable practices (Jia et al., 2021; Liu et al., 2021; Ma et al., 2021).

Some models integrate compliance considerations. Hua et al. (2016) propose a two-tier regulatory investment model. García-Alcaraz et al. (2020) demonstrate the role of ICT in improving SC performance under regulatory constraints. Tuladhar et al. (2024) and Bradley et al. (2025) underscore the importance of IT investment and compliance costs. Nevertheless, few existing models simultaneously optimize investments in technology and regulatory compliance by considering both as decision variables.

2.5. Environmental Sustainability and Regulation

Many recent models optimize regulatory compliance and technology investment with a focus on sustainability. For example, Benjaafar et al. (2012) incorporate carbon emissions into procurement, production, and inventory decisions, showing that emissions can be minimized through supply chain collaboration without increasing costs. Wang et al. (2017) apply game theory to analyze how supply chain enterprises respond to government policies, demonstrating that centralized systems improve profits and social welfare. Chalmardi and Camacho-Vallejo (2018) design a mixed-integer linear programming (MILP) model that incorporates financial incentives to promote the adoption of cleaner technologies, concluding that non-production-based incentives are more effective in reducing environmental impacts. Ma et al. (2021) propose an optimization model for investments in green technologies under cooperative strategies and regulatory constraints, highlighting the trade-offs between profits and stringent regulation. Similarly, Peng et al. (2022), Sun et al. (2023), and Cai and Jiang (2023) evaluate the effects of carbon pricing, cap-and-trade systems, and government subsidies on investment decisions and supply chain performance. Although technological investment and compliance with government regulations have been researched in SCM, no existing paper addresses their simultaneous optimization. Only a few models simultaneously optimize both variables within a general supply chain management context.

2.6. Research Gap and Contribution

From the literature review, two key points emerge: first, Monsreal et al. (2019) is the only study that proposes a mathematical model that optimizes both factors, but not simultaneously; second, there is a need for optimization models that jointly optimize technology investments and regulatory compliance simultaneously. This paper addresses this gap by developing a mathematical optimization model that simultaneously considers both variables within SCM.

3. Mathematical Optimization Model

The mathematical optimization model proposed in this paper builds upon the factors identified as relevant in Monsreal et al. (2019). More specifically, the two decision variables: technology level and government regulation level, are measured in monetary units. Such monetary measures are referred to as as “investment levels”. The model then optimizes R, I, and J (order efficiency, JIT efficiency, and operating efficiency, respectively) given a mix of technology and government regulation levels. The relevance of the variables considered in the proposed model is based on an international survey conducted by Monsreal et al. (2019). This survey collected data on end-to-end visibility of the supply chain, which involves the use of Auto-ID (Monsreal et al., 2019).

The findings of the survey identified four main factors such as quality, cost, technology adoption or use, and government regulations. Quality refers to functionality and performance; cost refers to all costs, including holding/inventory cost; technology adoption or use refers to the use of emerging technologies so that specific components of the supply chain can be optimized, and government regulations which refers to regulations, laws and other relationships established by local, state and federal governments.

As in Monsreal et al. (2019), this research contributes by explaining and specifying the connection between these four variables to increase the understanding of the effect of government regulation on technology adoption. However, the present study extends this work by proposing a new model that simultaneously optimizes the two target factors of technology adoption and government regulation in terms of investment levels. The other two major variables, quality and cost, are variables to assess the appropriate amount of such investment in government regulation and technology. Thus, the decision variables of the model are technology adoption ($T \geq 0$) and compliance with government regulations ($G > 0$), both measured in monetary terms: T, measured as investments in adopting new technology, and G, measured as investments in complying with government regulations.

The model’s input data parameters are presented in Table 1. These parameters include structural and operational characteristics of the SC such as fixed order cost per order cycle (O), annual demand (D), annual inventory holding cost per unit (H), and operating cost per unit (C). The model also defines lower (M) and upper (N) bounds for the ordering efficiency coefficient (R), lower (L) and upper (U) bounds for the JIT efficiency coefficient (I), and lower (A) and upper (E) bounds for the operating efficiency coefficient (J). Additionally, exponential sensitivity factors (β_1-β_6) are included to model how investments in technology adoption and in compliance with government

Table 1. Input parameters.

Symbol	Description	Range
O	Fixed ordering cost per order cycle [$]	O ≥ 0
D	Annual demand [shipments]	D ≥ 0
β_1	Technology exponential parameter for R	$\beta_1 \geq 0$
β_2	Government exponential parameter for R	$\beta_2 \geq 0$
β_3	Technology exponential parameter for I	$\beta_3 \geq 0$
β_4	Government exponential parameter for I	$\beta_4 \geq 0$
β_5	Technology exponential parameter for J	$\beta_5 \geq 0$
β_6	Government exponential parameter for J	$\beta_6 \geq 0$
H	Annual inventory holding cost per unit [$]	H ≥ 0
C	Operating cost per unit [$]	C ≥ 0
M	Lowest ordering efficiency coefficient (R) level	0 ≤ M < 1
N	Highest ordering efficiency coefficient (R) level	0 < N ≤ 1 or M < N ≤ 1
L	Lowest JIT efficiency coefficient (I) level	0 ≤ L < 1
U	Highest JIT efficiency coefficient (I) level	0 < U ≤ 1 or L < U ≤ 1
A	Lowest operating efficiency coefficient (J) level	0 ≤ A < 1
E	Highest operating efficiency coefficient (J) level	0 < E ≤ 1 or A < E ≤ 1

regulations affect each of these SC efficiency coefficients–R, I and J. The model's parameters are calibrated using empirical data and benchmark values reported in the literature.

The model's decision variables T and G, along with the input data parameters, determine the model´s efficiency coefficients R, I, and J, which are calculated by the model. Each efficiency coefficient is bounded between 0 and 1: the ordering efficiency coefficient (0≤R≤1), the JIT efficiency coefficient (0≤I≤1), and the operating efficiency coefficient (0≤J≤1). These coefficients capture how investments in technology adoption enhance performance, and how investments in compliance with government regulations may constrain SC performance. R, I, and J are used to calculate the optimal total cost (TC) and the optimal order quantity (Q*) under both cost-oriented and quality-oriented optimization objectives. The model's efficiency coefficients are defined as follows:

- Ordering efficiency coefficient (R): the degree to which the fixed ordering cost per order cycle decreases with investments in T and increases with investments in G.
- JIT efficiency coefficient (I): the degree to which delivery-to-consumption or production synchronization (i.e., time from delivery to consumption or production) improves with investments in T and worsens with investments in G.
- Operating efficiency coefficient (J): the degree to which unit operating costs decrease with investments in T and increase with investments in G.

The model's assumptions are:

- The fixed ordering cost is set at the beginning of each periodic order cycle and remains constant throughout the cycle.
- Total demand level is known and constant over the planning horizon.
- Investments in T increase R, I, and J by improving ordering processes, JIT performance, and operating conditions within the SC.
- Investments in G decrease R, I, and J by introducing operational constraints and additional compliance requirements in the SC.

Eq. 1 calculates the total cost function (TC), which integrates operational cost components–ordering, inventory holding, and operating costs–along with investments related to T and G. Eq. 1 is adapted from the SC RFID Investment Evaluation Model (Hua et al., 2016) and extends their approach by allowing the optimization of cost and quality performances under different technology-investment and government regulation-compliance scenarios. In this equation, the efficiency coefficients R and J are cost-oriented and directly affect the first and third terms, while the efficiency coefficient I is quality-oriented and influences the second term.

$$TC = \frac{ORD}{Q} + \frac{IHQ}{2} + JCD + T + G \tag{1}$$

Eq. 2 calculates the optimal order quantity (Q*) as a function of R, I and J. This equation links strategic investments in T and G to tactical and operational planning decisions. This equation considers the dynamic effects of investments in T and in G on SC efficiency, which is an advantage over the traditional Economic Order Quantity (EOQ) model, which assumes static cost parameters.

$$Q^* = \sqrt{\frac{2ORD}{HI}} \tag{2}$$

Eqs. 3, 4, and 5 calculate the model's efficiency coefficients R, I, and J based on the approach proposed by Azadeh et al. (2009). However, in this paper, R, I, and J are formulated as functions of T and G, allowing the proposed model to capture the impact of investing in T and the effects of investing in G on SC performance.

$$R = (N-M) + (M-N)e^{\beta_1 T} + \Big(N-M\Big)e^{\frac{1}{\beta_2 G}} \tag{3}$$

$$I = (U-L) + (L-U)e^{\beta_3 T} + \Big(U-L\Big)e^{\frac{1}{\beta_4 G}} \tag{4}$$

$$J = (E-A) + (A-E)e^{\beta_5 T} + \Big(E-A\Big)e^{\frac{1}{\beta_6 G}} \tag{5}$$

Eqs. 6, 7, 8 and 9 describe the technology-adoption and government-regulation cost-oriented optimization model, which simultaneously minimizes TC by determining the optimal investment levels in T and G. Eq. 6 is the cost-oriented total-cost function (TC_c) defined as a function of ordering cost, operating cost, and investment expenditures. Eq. 7 expresses TC_c as a function of T and G, Eqs. 8 and 9 define R and J as functions of T and G.

$$TC_c = \frac{ORD}{Q} + JCD + T + G \tag{6}$$

$$TC_c = f(T,G) \tag{7}$$

$$R = r(T,G) \tag{8}$$

$$J = j(T,G) \tag{9}$$

Eq. 10 analyzes how changes in T and G affect TCc (Eq. 6). We derive the TCC function with respect to T and G as $dTC_C = \frac{\partial f}{\partial T}dT + \frac{\partial f}{\partial G}dG$, knowing that TCc, R and J are functions of T and G (Eqs. 6 to 9) and applying the chain rule. Hence, Eq. 10 expresses the derivative of TCc with respect to R and J. This derivative captures how changes in R and J affect the total cost associated with operational performance, considering that R and J are functions of T and G (Eqs. 8 and 9).

$$dTC_c = \frac{O(\frac{\partial R}{\partial T})D}{Q} + 1 + \frac{O(\frac{\partial R}{\partial G})D}{Q} + 1 + \frac{\partial J}{\partial T}CD + 1 + \frac{\partial J}{\partial G}CD + 1 \tag{10}$$

Eq. 11 presents the derivative of the TCc function (dTCc), which considers the effects of R and J.

$$dTC_c = 4 + \frac{OD}{Q}\big(\frac{\partial R}{\partial T} + \frac{\partial R}{\partial G}\big) + CD\big(\frac{\partial J}{\partial T} + \frac{\partial J}{\partial G}\big) \tag{11}$$

To analyze how changes in T and G affect R, we substitute Eq. 3 into Eq. 8, yielding Eq. 12, which expresses the derivative of the efficiency coefficient R (dR) based on exponential response to T and G.

$$dR = \beta_1(M-N)e^{\beta_1 T} - \frac{(N-M)e^{\frac{1}{\beta_2 G}}}{\beta_2 G^2} \tag{12}$$

By setting Eq. 11 equal to zero–applying the first-order condition for optimization–Eq. 13 expresses how much R must change to minimize TCc given the values of O, D, C, and Q, as well as the derivative of the model's efficiency coefficient J (dJ).

$$dR = -\big(\frac{4+CDdJ}{OD}\big)Q \tag{13}$$

Eq. 14 results from substituting Eq. 12 into Eq. 13. It expresses dR as a function of T and G, linking these decision variables with dJ to estimate the marginal-cost trade-offs between enhancing efficiency through investments in T and in G.

$$\beta_1(M-N)e^{\beta_1 T} - \frac{(N-M)e^{\frac{1}{\beta_2 G}}}{\beta_2 G^2} = -\big(\frac{4+CDdJ}{OD}\big) \tag{14}$$

Eq. 15 results from substituting Eq. 2 in Eq. 14. This equation calculates the optimal ordering efficiency (R*) as a function of T and G. Therefore, Eq. 15 incorporates the effects of investments in T and in G to estimate R*.

$$R^* = \left[\frac{-\beta_1(M-N)e^{\beta_1 T} + \frac{\left(N-M\right)e^{\frac{1}{\beta_2 G}}}{\beta_2 G^2}}{4+CD\left(\beta_5(A-E)e^{\beta_5 T} - \frac{(E-A)e^{\frac{1}{\beta_6 G}}}{\beta_6 G^2}\right)}\right]^2 \frac{ODHI}{2} \tag{15}$$

Eq. 16 calculates the optimal technology-adoption level (T*) as a function of R* and G.

$$T^* = \frac{\ln\left(\frac{R^* - N + M - \left(N-M\right)e^{\frac{1}{\beta_2 G}}}{(M-N)}\right)}{\beta_1} \tag{16}$$

Eq. 17 calculates the optimal government-regulation level (G^*) as a function of R^* and T.

$$G^* = \ln\left(\frac{R^* - N + M - (M-N)e^{\beta_1 T}}{(N-M)}\right)\beta_2 \tag{17}$$

Eqs. 16 and 17 close the optimization loop by linking the model's decision variables T and G to the model's efficiency coefficients R, I and J.

Eqs. 18 to 20 define the technology-adoption and government-regulation quality-oriented optimization model. Eq. 18 expresses the quality-oriented total-cost function (TC_Q), defined as a function of inventory holding cost. Equation 19 expresses TC_Q as a function of T and G, and Eq. 20 defines I as a function of T and G. These equations show how investments in T impact the quality performance of SC.

$$TC_Q = \frac{IHQ}{2} + T + G \tag{18}$$

$$TC_Q = g(T, G) \tag{19}$$

$$I = i(T, G) \tag{20}$$

Eq. 21 analyzes how changes in T and G affect TC_Q. This equation is the derivative of Eq. 18 with respect to T and G as $dTC_Q = \frac{\partial f}{\partial T}dT + \frac{\partial f}{\partial G}dG$, knowing that TC_Q and I are functions of T and G (Eqs. 18 to 20) and applying the chain rule. Hence, Eq. 21 expresses the derivative of TC_Q with respect to I. This equation captures how changes in I affect the total cost associated with quality performance, considering that I is function of T and G (Eqs. 19 and 20).

$$dTC_Q = 2 + \frac{HQ}{2}dI \tag{21}$$

By setting Eq. 21 equal to zero–applying the first-order condition for optimization–Eq. 22 expresses how much I must change to minimize TC_Q given the values of H and Q.

$$dI = -\frac{4}{HQ} \tag{22}$$

Eq. 23 results from substituting Eqs. 4 and 20 into Eq. 22. This equation defines the derivative of the model's efficiency coefficient I (dI) as a function of T and G. This equation links changes in T and G to the first-order optimization condition for minimizing TC_Q.

$$dI = \beta_3(L-U)e^{\beta_3 T} - \frac{\left(U-L\right)e^{\frac{1}{\beta_4 G}}}{\beta_4 G^2} \tag{23}$$

Then, Eq. 24 is obtained by setting Eq. 23 equal to Eq. 22. This equation links the marginal effect of T and G on the efficiency coefficient I to the quality-related total-cost minimization condition.

$$\beta_3(L-U)e^{\beta_3 T} - \frac{(U-L)e^{\frac{1}{\beta_4 G}}}{\beta_4 G^2} + \frac{4}{HQ} = 0 \tag{24}$$

Eq. 25 results from substituting Eq. 2 into Eq. 24. It shows the substitution of Q^* into Eq. 24. This equation expresses the optimal JIT efficiency coefficient (I^*) as a function of T and G, linking strategic investment decisions in T to quality-related cost performance.

$$I^* = \frac{8}{H^2\left(\beta_3(L-U)e^{\beta_3 T} - \frac{(U-L)e^{\frac{1}{\beta_4 G}}}{\beta_4 G^2}\right)^2}\left(\frac{H}{ORD}\right) \tag{25}$$

Eq. 26 calculates the optimal operating-efficiency coefficient (J^*) by substituting the optimal values of T^* and G^*–derived from Eqs. 16 and 17–into the model's operating efficiency coefficient function (Eq. 5). This function links J^* to strategic investment decisions in T and in G completing the quality-oriented optimization model.

$$J^* = (E-A) + (A-E)e^{\beta_5 T^*} + \left(E-A\right)e^{\frac{1}{\beta_6 G^*}} \tag{26}$$

In summary, the optimal equations of the simultaneous Technology-Adoption and Government-Regulation quality-oriented optimization model are Eqs. 15, 16, 17, 25, and 26.

4. Results

4.1 Case Study

This paper uses the same data collected from a German container consignee company, as used in Monsreal et al. (2019), to test the proposed simultaneous optimization model.

Four scenarios are designed to test the currently proposed optimization model.

- Scenario 1: both investments in technology adoption (T, measured as investments in technology), and investments in compliance with government regulations (G, measured as compliance costs) are increased. Figures 1, 2 and 3 represent this scenario.
- Scenario 2: total investment is maintained constant at 11%, while the shares between investments in technology adoption (T, measured as technology investments) and investments in compliance with

government regulations (G, measured as compliance costs) varies. Figures 4, 5 and 6 represent this scenario.

- Scenario 3 analyzes the impact of increasing investments in technology adoption (T, measured as technology investments) while maintaining constant investments in compliance with government regulations (G, measured as compliance costs) at a minimum. Figures 7, 8 and 9 represent this scenario.
- Scenario 4 analyzes the impact of increasing investments in compliance with government regulations (G, measured as compliance costs) while maintaining constant investments in technology adoption (T, measured as technology investments) at their minimum level. Figures 10, 11 and 12 represent this scenario.

Table 2 shows the specific scenarios with their corresponding values.

Table 2. Design of the experiment.

Scenario 1		Scenario 2		Scenario 3		Scenario 4	
G (%)	T (%)	G (%)	T (%)	G (%)	T (%)	G (%)	T (%)
1	1	10	1	1	1	1	1
2	2	9	2	1	2	2	1
3	3	8	3	1	3	3	1
4	4	7	4	1	4	4	1
5	5	6	5	1	5	5	1
6	6	5	6	1	6	6	1
7	7	4	7	1	7	7	1
8	8	3	8	1	8	8	1
9	9	2	9	1	9	9	1
10	10	1	10	1	10	10	1

For this purpose, the initial values for the model's decision variables (T and G), efficiency coefficients (R, T and J), and exponential sensitivity factors (β1-β6) are the same as those used by Monsreal et al. (2019) and are reproduced in Table 3 for reference. Similarly, an investment threshold of 10% of total operating cost, for both investments in T and G optimization, is used, considering a total annual operating cost of approximately USD 4 million (Monsreal et al., 2019). This 10% threshold serves as the reference for the design of the experiment.

Input values for efficiency coefficients (R, T and J), and exponential sensitivity factors (β1-β6) are based on Monsreal et al. (2019).

The higher the values of R, T and J are, the greater the benefits obtained from investing in technology adoption (T).

4.2 Results

Figures 1 to 12 present the results obtained from the four scenarios. These figures illustrate the behavior of R, T and J under each scenario.

Scenario 1 (Figures 1 to 3) analyzes the effects of jointly increasing investments in T and G from 1% to 10% of total operating cost. Figure 1 shows that R initially increases as investments in T and G rise, but R plateaus at 8% level, suggesting diminishing marginal returns. Beyond this percentage of the total operating cost, further investments in T and G do not produce additional gains in R, likely due to saturation effects in automation or coordination processes.

Table 3. Model variables, coefficients, and exponential parameters

Variable	Description	Value	Units
O	Fixed ordering cost per order cycle	75.5	USD
D	Annual demand	11,200.00	Trips
H	Annual inventory cost per unit	81.48	USD
C	Operating cost per unit	257.99	USD
M	Lowest ordering efficiency coefficient (*R*) level	0.3	-
N	Highest ordering efficiency coefficient (*R*) level	1	-
L	Lowest JIT efficiency coefficient (*I*) level	0.2	-
U	Highest JIT efficiency coefficient (*I*) level	1	-
A	Lowest operating efficiency coefficient (*J*) level	0.5	-
E	Highest operating efficiency coefficient (*J*) level	1	-
β1	Technology exponential parameter for *R*	0.00002	-
β2	Government exponential parameter for *R*	-0.00002	-
β3	Technology exponential parameter for *I*	0.00001	-
β4	Government exponential parameter for *I*	-0.00001	-
β5	Technology exponential parameter for *J*	0.00002	-
β6	Government exponential parameter for *J*	-0.00002	-

Figure 2 shows that I decrease as investments in T and G increase simultaneously. This decline is likely due to disruptions in synchronization between delivery and production, such as rigid compliance protocols or misalignment between the implementation of new technologies and operational execution.

Figure 3 shows that J also decreases when investments in T and G increase. This indicates that investments in T and G may raise unit operating costs instead of reducing them.

Figures 1 to 3 indicate that increasing investments in T and G does not always improve SC performance–unless these investments are optimally balanced. On one hand, R improves initially but plateaus around 8%, offering no additional gains beyond that level. On the other hand, I and J decline as investments increase. Scenario 1 suggests that increasing investment costs can lead to inefficiencies and trade-offs, rather than performance improvements.

Scenario 2 (Figures 4 to 6) analyzes the effects of varying the investment mix between T and G while keeping total investment constant at 11%. Figure 4 shows that R reaches its highest value when T is at 1% and G at 10% of the total operating cost. As investment in T increases and investment in G decreases, R declines. This result suggests that ordering processes benefit more from investing in G than from investing in T.

Figure 5 shows that the best performance of I occurs when T is low and G is high–specifically, when T is at 1% and G at 10% of the total operating cost. This result highlights that, with total investment fixed at 11%, investing in G improves delivery-to-production synchronization more effectively than investing in T.

Figure 6 shows that operating efficiency (J) improves as investment in T increases and investment in G decreases. The best result for J occurs when T is at 10% and G at 1% of the total operating cost. This result suggests that J depends more directly on T and is negatively impacted by G.

Figures 4 to 6 show that setting the optimal balance between investments in T and G–while keeping the total investment constant at 11%–produces different results across R, I and J. The performance of R and I improves as investment in G increases and investment in T decreases, reaching their peaks when G is high and T is low. This result suggests that investment in G drives improvements in R and I. In contrast, J improves as investment in T increases, reaching its highest level when T is high and G is low. Scenario 2 highlights that performance improvements

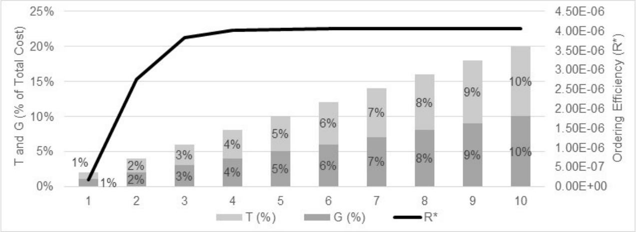

Figure 1. Ordering Efficiency (R) Scenario 1.

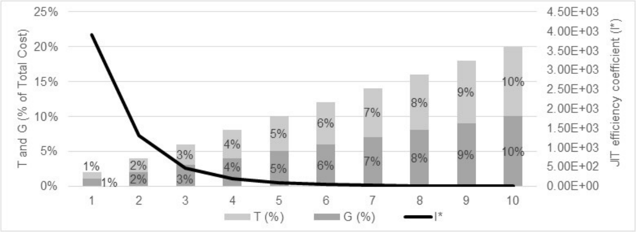

Figure 2. JIT Efficiency Scenario 1.

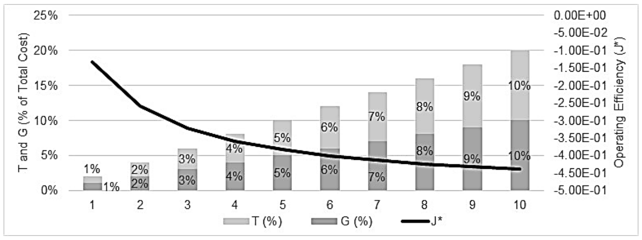

Figure 3. Operating Efficiency Scenario 1.

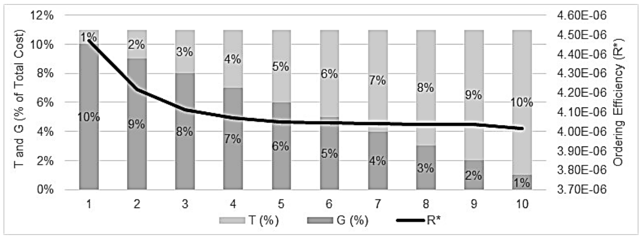

Figure 4. Ordering Efficiency Scenario 2.

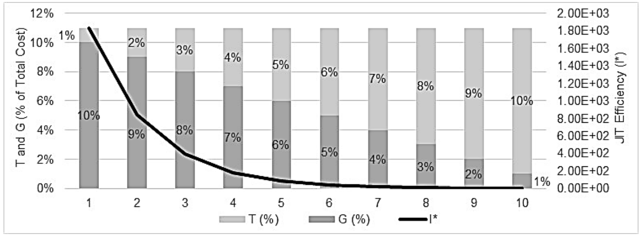

Figure 5. JIT Efficiency Scenario 2.

depend not just on how much is invested overall, but on how much investment is distributed between T and G.

Scenario 3 (Figures 7 to 9) studies the effects of increasing investment in T while keeping constant investment in G at a minimum. Figure 7 shows that R increases as T increases, indicating that ordering functions are highly related to technological improvements even in the absence of government regulation constraints. This result suggests that upgrades in T–such as automation, digital ordering systems, or real-time communication platforms–directly enhance order processing and coordination across the SC.

Figure 8 shows that I decreases as investments in T increase. This result suggests that investing in T may lead to desynchronization between supply and production when investments are not optimally balanced with investments in G. A possible interpretation of this is that the adaptation to new technologies may outpace internal operations, causing inefficiencies in timing or coordination. Without government regulation constraints, adoption of new technologies might disrupt rather than streamline JIT alignment.

Figure 9 shows that J increases as investments in T increase. This result is expected, as technologies tend to minimize unit production costs, optimize resource use, and enhance overall process efficiency. Even when investments in G are minimal, these benefits accumulate, demonstrating the importance of investing in T.

Figures 7 to 9 show that increasing investments in T, while keeping investments in G at a minimum, leads to different results across R, I, and J. On the one hand, R and J improve constantly as investments in T increase. These efficiency coefficients show clear improvements from investing in T. On the other hand, I decreases as investments in T increase. This result suggests a probable misalignment between T and production-delivery synchronization. Scenario 3 reveals that investing in T alone can improve certain aspects of SC performance but may also introduce trade-offs if it is not optimally balanced with G.

Scenario 4 (Figures 10 to 12) studies the impact of increasing investments in G while keeping constant investments in T at a minimum. Figure 10 shows that R improves as G increases. This result suggests that some government regulations streamline ordering processes and enhance their efficiency, despite the additional investments in G.

Figure 11 shows that I decreases as G increases. This decline could likely reflect the challenges that government regulations impose on synchronizing delivery and

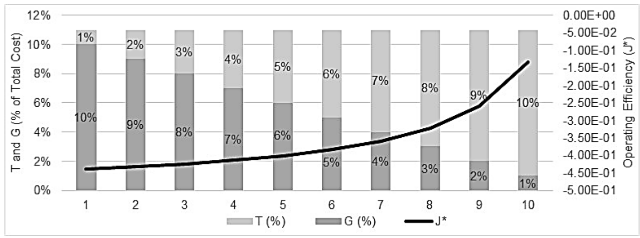

Figure 6. Operating Efficiency Scenario 2.

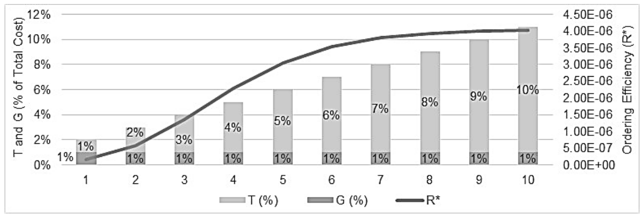

Figure 7. Ordering Efficiency Scenario 3.

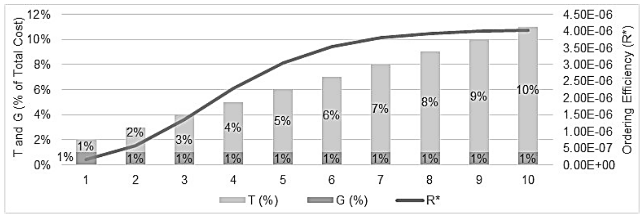

Figure 8. JIT Efficiency Scenario 3.

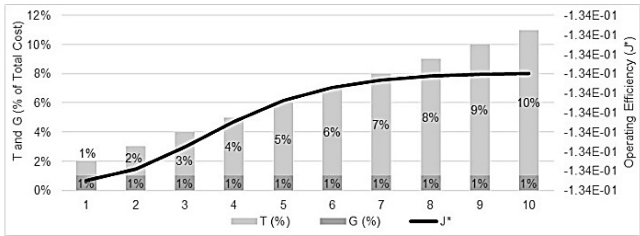

Figure 9. Operating Efficiency Scenario 3.

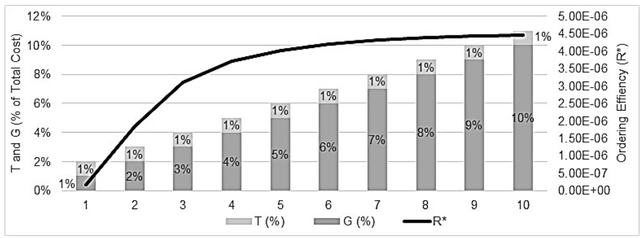

Figure 10. Ordering Efficiency Scenario 4.

production schedules, causing operations to become less flexible or slower.

Figure 12 shows that J also declines as investments in G increase. This result indicates that increasing investments in G raises unit operating costs, negatively impacting J.

Figures 10 to 12 show the effects of increasing investments in G while keeping constant investments in T at a minimum. R improves as investments in G increase, and this result suggests that certain government regulations can streamline ordering processes despite added investment costs. However, both I and J decline with higher investments in G, reflecting challenges in delivery-production synchronization and increased unit operating costs. Scenario 4 highlights that while compliance with government regulations may benefit some of the SC functions, it can also introduce inefficiencies and trade-offs in others when investments in T are low.

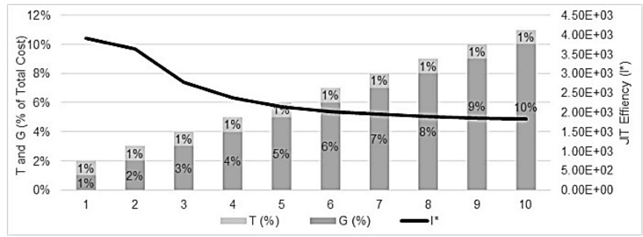

Figure 11. JIT Efficiency Scenario 4.

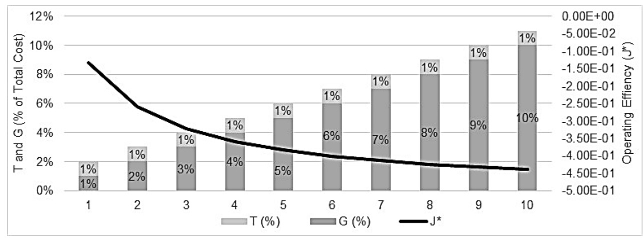

Figure 12. Operating Efficiency Scenario 4.

4.3 Discussion on Scenario Use and Interpretation

Investments in technology adoption are a variable that can be controlled by private companies through their operations and strategic management decisions, while government regulations are designed, enacted, and issued by public authorities, and they often require investments in compliance with government regulations from companies. Therefore, the way to use and interpret these results depends on the purpose and user profile.

From the perspective of companies, Scenario 1 facilitates the identification of the optimal allocation between investing in technology adoption and compliance with government regulations, assuming both contribute equally to the total investment level.

Scenario 2 offers a supplementary progression of investment contributions between technology and government regulation compliance. The results from this scenario guide companies toward the right balance between these two investment types.

Scenario 3 provides a baseline to understand the impact of overall increases in technological investment. Thus, this scenario enables companies to evaluate which types of operational efficiencies are most influenced by investing in technology adoption. These scenarios help companies strategically target areas that maximize returns on technological investments by isolating their effects.

From a governmental or policymaking point of view, Scenario 4 mimics the Scenario 3 baseline approach but keeps technology investment steady while increasing government regulation compliance investment. This scenario evaluates the broader impact of regulatory policies on industry performance by assessing how different levels of regulatory stringency affect companies' operational efficiency. Governments can use the results of this scenario to design more effective and less disruptive regulations. As with companies, a government could benefit from the results obtained in Scenario 1 when it seeks to understand the overall effects of aggregated investments.

The main contribution of the proposed model is its capacity to simultaneously optimize investments in technology and compliance with government regulations. By doing so, this two-decision-variable optimization model is different from the single-decision-variable model published by Monsreal et al. (2019).

The results of the four scenarios reveal counterintuitive outcomes—such as perceived benefits from government regulations and negative impacts from technology investments. The comparison of the results suggests that certain types of efficiency may be more (or less) sensitive to specific types of investments. For example, on the one hand, the efficiency associated with just-in-time (JIT) logistics may not respond strongly to technology investment because its benefits are time-based, and such improvements may not be fully captured in costs. The behavior of JIT efficiency remains consistent across the four scenarios, supporting this analysis. On the other hand, ordering efficiency improves under government regulation–possibly due to a decrease in demand (interpreted in this model as sales), which lowers the order cost per cycle and thus increases efficiency.

Operating efficiency improves under technology investment and weakens under stricter regulatory scenarios (Scenarios 2, 3, and 4), as well as under increasing total investments. This analysis suggests that operating efficiency is very sensitive to the balance and scale of technology and compliance with government regulation investments.

Conclusions

This paper proposes a mathematical optimization model that simultaneously optimizes investments in technology and compliance with government regulations in SCM. This paper tackles a critical gap in the SCM literature and provides a more comprehensive and realistic decision-making tool for both private firms and policymakers.

Through a real case study and the analysis of four scenarios, the proposed optimization model demonstrates that operational efficiencies—such as ordering, JIT, and general operating efficiency—respond differently to variations in technology adoption and compliance with government regulation investments. The results reveal counterintuitive effects, including negative impacts due to the potential inefficiencies from excessive technology investments, and positive impacts of moderate regulations. These results emphasize the importance of finding the optimal equilibrium between both variables rather than optimizing them independently.

The proposed optimization model provides strategic insights for companies aiming to enhance competitiveness while ensuring compliance with government regulations. Similarly, it offers governments and/or policymakers a framework for designing policies that promote the adoption of new technologies without compromising operational performance.

One future line of research would be to compare and empirically validate the results obtained in this paper by using data from other industries and countries, which would further strengthen the model's applicability and generalizability.

Our results are constrained to the specific case study and therefore to the data used for the presented analysis. Therefore, future research could extend this model by incorporating uncertainty, multi-echelon supply chains, or dynamic regulatory environments.

A third proposed line of research is to add other decision variables to the proposed model, such as sustainability initiatives, risk mitigation strategies, or digital transformation investments.

Finally, a future study could be conducted to explore a dynamic extension of the model, where investment decisions evolve over time.

Conflict of interest

The authors do not have any type of conflict of interest to declare.

Funding

The authors did not receive any sponsorship to carry out the research reported in the present manuscript.

References

Atkin, D., Chaudhry, A., Chaudry, S., Khandelwal, A. K., & Verhoogen, E. (2017). Organizational Barriers to Technology Adoption: Evidence from Soccer-Ball Producers in Pakistan*. *The Quarterly Journal of Economics*, *132*(3), 1101–1164. https://doi.org/10.1093/qje/qjx010

Azadeh, A., Keramati, A., & Songhori, M. J. (2009). An integrated Delphi/VAHP/DEA framework for evaluation of information technology/information system (IT/IS) investments. *The International Journal of Advanced Manufacturing Technology*, *45*(11–12), 1233–1251. https://doi.org/10.1007/s00170-009-2047-2

Benjaafar, S., Li, Y., & Daskin, M. (2012). Carbon Footprint and the management of supply chains: Insights from simple models. *IEEE Transactions on Automation Science and Engineering*, *10*(1), 99–116. https://doi.org/10.1109/tase.2012.2203304

Blaettchen, P., Calmon, A. P., & Hall, G. (2024). Traceability Technology adoption in supply chain networks. *Management Science*. https://doi.org/10.1287/mnsc.2022.01759

Bradley, R. V., Bichescu, B. C., Cha, J., Bell, J. E., Esper, T., & Hazen, B. (2025). Where does insensitivity lie? How IT investment decision practices shape supply chain efficiency. *Journal of Business Logistics*, *46*(1). https://doi.org/10.1111/jbl.70001

Brehm, J., & Hamilton, J. T. (1996). Noncompliance in environmental reporting: Are violators ignorant, or evasive, of the law? *American Journal of Political Science*, *40*(2), 444. https://doi.org/10.2307/2111632

Chalmardi, M. K., & Camacho-Vallejo, J. (2018). A bi-level programming model for sustainable supply chain network design that considers incentives for using cleaner technologies. *Journal of Cleaner Production*, *213*, 1035–1050. https://doi.org/10.1016/j.jclepro.2018.12.197

Charoenwong, B., Kowaleski, Z. T., Kwan, A., & Sutherland, A. G. (2024). RegTech: Technology-driven compliance and its effects on profitability, operations, and market structure. *Journal of Financial Economics*, *154*, 103792. https://doi.org/10.1016/j.jfineco.2024.103792

Chiang, A., Trimi, S., & Kou, T. (2024). Critical factors for Implementing Smart Manufacturing: A Supply Chain perspective. *Sustainability*, *16*(22), 9975. https://doi.org/10.3390/su16229975

Cai, J., & Jiang, F. (2023). Decision models of pricing and carbon emission reduction for low-carbon supply chain under cap-and-trade regulation. *International Journal of Production Economics*, *264*, 108964. https://doi.org/10.1016/j.ijpe.2023.108964

Doerr, K. H., Gates, W. R., & Mutty, J. E. (2006). A hybrid approach to the valuation of RFID/MEMS technology applied to ordnance inventory. *International Journal of Production Economics*, *103*(2), 726–741. https://doi.org/10.1016/j.ijpe.2006.03.007

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., Foropon, C., & Papadopoulos, T. (2023). Dynamic digital capabilities and supply chain resilience: The oole of government effectiveness. *International Journal of Production Economics*, *258*, 108790. https://doi.org/10.1016/j.ijpe.2023.108790

Khoury, R. E., Alshater, M. M., & Joshipura, M. (2024). RegTech advancements-a comprehensive review of its evolution, challenges, and implications for financial regulation and compliance. *Journal of Financial Reporting & Accounting*. https://doi.org/10.1108/jfra-05-2024-0286

Ezeigweneme, C.A., Umoh, A.A., Ilojianya, V.I., & Adegbite, A.O. (2024). Review of telecommunication regulation and policy: comparative analysis USA and Africa. *Computer Science & IT Research Journal, 5(1)*, 81-99. https://doi.org/10.51594/csitrj.v5i1.703

García-Alcaraz, J.L., Martínez-Loya, V., Díaz-Reza, J.R., Blanco-Fernández, J., Jiménez-Macías, E., & Gil López, A.J. (2020). Effect of ICT integration on SC flexibility, agility and company' performance: the Mexican maquiladora experience. *Wireless Networks, 26*, 4805–4818. https://doi.org/10.1007/s11276-019-02068-6

Gaukler, G. M., Seifert, R. W., & Hausman, W. H. (2007). Item-level RFID in the retail supply chain. *Production and Operations Management, 16(1)*, 65-76. https://doi.org/10.1111/j.1937-5956.2007.tb00166.x

Ghiassi, M., & Spera, C. (2003). Defining the Internet-based supply chain system for mass customized markets. *Computers & Industrial Engineering, 45(1)*, 17–41. https://doi.org/10.1016/S0360-8352(03)00017-2

Gray, W., & Shadbegian, R. (2021). Economics of environmental compliance and enforcement. *In Oxford Research Encyclopedia of Environmental Science. Oxford University Press*. https://doi.org/10.1093/acrefore/9780199389414.013.444

Gunasekaran, A., & Ngai, E.W.T. (2004). Information systems in supply chain integration and management. *European Journal of Operational Research, 159(2)*, 269–295. https://doi.org/10.1016/j.ejor.2003.08.016

Heese, H.S. (2007). Inventory record inaccuracy, double marginalization, and RFID adoption. *Production and Operations Management, 16(5)*, 542-553. https://doi.org/10.1111/j.1937-5956.2007.tb00279.x

Hofmann, E., & Rüsch, M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. *Computers in Industry, 89,* 23–34. https://doi.org/10.1016/j.compind.2017.04.002

Hua, Z., Chen, W., & Zhang, Z. G. (2016). Competition and coordination in two-tier public service systems under government fiscal policy. *Production and Operations Management, 25(8)*, 1430-1448. https://doi.org/10.1111/poms.12555

Huang, H., Yang, J., & Ren, C. (2024). Unlocking ESG performance through intelligent manufacturing: The roles of transparency, green innovation, and supply chain collaboration. *Sustainability, 16(23)*: 10724. https://doi.org/10.3390/su162310724

Ibiyeye, T.O., Iornenge, J.T., & Adegbite, A. (2024). Evaluating regulatory compliance in the finance and investment sector: An analysis of current practices, challenges, and the Impact of emerging technologies. *Iosr Journal of Economics and Finance, 15(6)*, 1-8 https://doi.org/10.9790/5933-1506010108

Jia, L., Nam, E., & Chun, D. (2021). Impact of Chinese government subsidies on enterprise innovation: Based on a three-dimensional perspective. *Sustainability, 13(3)*:1288. https://doi.org/10.3390/su13031288

Kocatepe, A., Ozkul, S., Ozguven, E. E., Sobanjo, J. O., & Moses, R. (2020). The value of freight accessibility: a spatial analysis in the Tampa Bay region. *Applied Spatial Analysis and Policy, 13*, 527–546.
https://doi.org/10.1007/s12061-019-09314-6

Konno, H., & Yamazaki, H. (1991). Mean-absolute deviation portfolio optimization model and its applications to Tokyo stock market. *Management science, 37(5)*, 519-531.
https://www.jstor.org/stable/2632458

Lee, K.L., Teong, C.X., Alzoubi, H.M., Alshurideh, M.T., Khatib, M.E., & Al-Gharaibeh, S.M. (2024). Digital supply chain transformation: The role of smart technologies on operational performance in manufacturing industry. *International Journal of Engineering Business Management. 16*, 1-19.
https://doi.org/10.1177/18479790241234986

Li, M., Cao, G., Cui, L., Liu, X., & Dai, J. (2023). Examining how government subsidies influence firms' circular supply chain management: The role of eco-innovation and top management team. *International Journal of Production Economics, 261*: 108893.
https://doi.org/10.1016/j.ijpe.2023.108893

Li, K., Dai, G., Xia, Y., Mu, Z., Zhang, G., & Shi, Y. (2022). Green technology investment with data-driven marketing and government subsidy in a platform supply chain. *Sustainability, 14*(7), 3992.
https://doi.org/10.3390/su14073992

Liu, L., Wang, Z., & Zhang, Z. (2021). Matching-game approach for green technology investment strategies in a supply chain under environmental regulations. *Sustainable Production and Consumption, 28*, 371-390.
https://doi.org/10.1016/j.spc.2021.06.001

Kauffman, R.J., Liu, J., & Ma, D. (2015). Technology investment decision-making under uncertainty. *Information Technology and Management, 16,* 153–172.
https://doi.org/10.1007/s10799-014-0212-2

Ma, S., He, Y., Gu, R., & Li, S. (2021). Sustainable supply chain management considering technology investments and government intervention. *Transportation Research Part E: Logistics and Transportation Review, 149*:102290.
https://doi.org/10.1016/j.tre.2021.102290

Menon, N.M., & Lee, B. (2000). Cost control and production performance enhancement by IT investment and regulation changes: evidence from the healthcare industry. *Decision Support Systems, 30(2),* 153-169.
https://doi.org/10.1016/S0167-9236(00)00095-6

Monsreal, M., Cruz-Mejia, O., Ozkul, S., & Saucedo-Martínez, J.A. (2019). An optimization model for investment in technology and government regulation. *Wireless Networks,* 1-13.
https://doi.org/10.1007/s11276-019-01958-z

Nadirsyah, M.I., & Mulyany, R. (2024). Enhancing fraud prevention and internal control: the key role of internal audit in public sector governance. *Cogent Business & Management, 11(1)*, 23-42.
https://doi.org/10.1080/13597566.2021.1998006

Peng, J., Chen, L., & Zhang, B. (2022). Transportation planning for sustainable supply chain network using big data technology. *Information Sciences, 609*, 781-798.
https://doi.org/10.1016/j.ins.2022.07.112

Perold, A.F. (1984). Large-scale portfolio optimization. *Management science, 30(10)*, 1143-1160.
https://doi.org/10.1287/mnsc.30.10.1143

Rai, A., Patnayakuni, R., & Seth, N. (2007). Firm performance impacts of digitally-enabled supply chain integration capabilities. *MIS Quarterly, 30(2)*, 225–246.
https://doi.org/10.2307/25148787

Raza, S.A. (2022). A systematic literature review of RFID in supply chain management, *Journal of Enterprise Information Management, 35(2)*, 617-649.
https://doi.org/10.1108/JEIM-08-2020-0322

Sarac, A., Absi, N., & Dauzère-Pérès, S. (2010). A literature review on the impact of RFID technologies on supply chain management. *International Journal of Production Economics, 128(1),* 77-95.
https://doi.org/10.1016/j.ijpe.2010.07.039

Selvaraj, M. (2025). Beyond compliance: Leveraging regulatory compliance to drive innovation in food supply chain traceability. *International Journal of Supply Chain and Logistics, 9(2)*, 18–29.
https://doi.org/10.47941/ijscl.2491

Shimshack, J., & Ward, M.B. (2008). Enforcement and over-compliance. *Journal of Environmental Economics and Management, 55(1)*, 90-105.
https://doi.org/10.1016/j.jeem.2007.05.003

Soori, M., Arezoo, B., & Dastre, R. (2023). Internet of things for smart factories in industry 4.0, a review. *Internet of Things and Cyber-Physical Systems, 3*, 192-204.
https://doi.org/10.1016/j.iotcps.2023.04.006

Sun, X., Wang, Y., Li Y., Zhu, W., Yan, D., & Li, J. (2023). Optimal pricing and carbon emission reductions for a prefabricated building closed-loop supply chain under a carbon cap-and-trade regulation and government subsidies. *PLoSONE, 18(6)*: e0287684.
https://doi.org/10.1371/journal.pone.0287684

Tuladhar, A., Rogerson, M., Engelhart, J., Parry, G.C., & Altrichter, B. (2024), Blockchain for compliance: an information processing case study of mandatory supply chain transparency in conflict minerals sourcing. *Supply Chain Management, 29(4)*, 755-777.
https://doi.org/10.1108/SCM-11-2023-0585

Wang, B., Lin, Z., Wang, M., Wang, F., Xiangli, P., & Li, Z. (2022). Applying blockchain technology to ensure compliance with sustainability standards in the PPE multi-tier supply chain. *International Journal of Production Research, 61(14)*, 4934–4950.
https://doi.org/10.1080/00207543.2022.2025944

Wang, C., Wang, W., & Huang, R. (2017). Supply chain enterprise operations and government carbon tax decisions considering carbon emissions. *Journal of Cleaner Production, 152,* 271-280.
https://doi.org/10.1016/j.jclepro.2017.03.051

Won, D., & Park, Y. (2020). Smart factory adoption in small and medium-sized enterprises: Empirical evidence of the manufacturing industry in Korea. *Technological Forecasting and Social Change, 157*:120117.
https://doi.org/10.1016/j.techfore.2020.120117

You, C. J., Lee, C. K., Chen, S., & Jiao, R. J. (2012). A real option theoretic fuzzy evaluation model for enterprise resource planning investment. *Journal of Engineering and Technology, 29(1)*, 47–61.
https://doi.org/10.1016/j.jengtecman.2011.09.005

Zandi, F., & Tavana, M. (2011). A fuzzy goal programming model for strategic information technology investment assessment. *Benchmarking: An International Journal, 18(2)*, 172-196.
https://doi.org/10.1108/14635771111121667