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An optimization model for investment in technology and government regulation

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Abstract

Companies struggle every day to estimate the adequate level of investment in new technologies, and governments lack the tools to determine the impact of their regulations on industry including telecommunications networks. Despite these facts, few studies discuss ways to assess appropriate levels of investment for technological initiatives and government regulations. To fill this gap, this study provides an optimization model for the investment of technology and government regulation, based on efficiencies. Results obtained from surveying northern European companies support the importance of estimating investment in technology and government regulation levels. The survey identified the four most relevant factors for practitioners: quality, cost, technology adoption, and government regulations. Based on the survey's results, the model evaluates the level of investment for technology adoption and government regulations using cost and quality as target variables. Additional data from a German carrier served to test the model. Results show that technology investment delivers more benefits in cost and quality by increasing technology adoption. However, the model also suggests that diminishing returns make efficiencies stall at a certain level of technology adoption, and shows an investment threshold dependent on the type of benefit, cost, or quality the company seeks to maximize. Regarding government regulation, the model shows a counterintuitive behavior at higher levels of investment for the cost coefficients and at all levels of investment for the quality coefficient. This suggests that government regulation effects could be shifting from fixed-order cost to other types of costs.

Keywords Telecommunications industry · Technology adoption · Government regulation · Investment · Optimization

1 Introduction

This paper develops a quantitative model to assess optimal levels of technology investment and government regulation investment—or compliance—in the industry. *Technology investment* is defined as the amount of economic or monetary resources an organization uses to purchase, develop, and/or implement technology. Technology adoption is usually positive for companies, but the level of impact from technology implementation varies. Critical questions for companies are: What is the level of technology adoption that delivers the most benefit for the organization? How much should the organization spend on technology? What is the adequate level of technology adoption considering the amount of investment companies put into technology solutions and the benefits derived from such technology?

Similarly, *government regulation investment* is defined as the amount of economic or monetary resources an organization uses to comply with such regulations. Even though the level of government regulation is not a company's decision, understanding the optimal level of investment companies make to comply with regulations opposed to the lost benefits or detriments in their operation could be a valuable tool for public agencies that seek a balance between economic growth and industry order.

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The proposed model is based on a set of factors, deemed relevant by a survey of companies located in northern Europe. The survey obtained information on the adoption of end-to-end supply chain visibility, which entails using automatic identification technologies (auto-ID). The auto-ID concept is an ample set of machine technologies that identifies objects and auto-collects data. The main objective of auto-ID is to increase efficiency through enhanced monitoring and object control, which reduces errors in data entry and lessens information gaps.

The survey results identified the four most important factors:

- Quality: functionality and performance, including inventory-holding time.
- Cost: all major costs including price and life-cycle costs.
- Technology adoption or use: the use of new technologies to optimize a certain process or processes of the supply chain [1].
- Government regulations: the laws, regulations, and relationships approved by the government [3].

The importance of this study lies in the critical role investment plays in technology implementation and government regulation compliance. For instance, the list of requirements for designing, selecting, and implementing an auto-ID system is long; this list ranges from technical knowledge to process mapping and expertise building. In any technology-related system, investment cost is critical for its successful implementation, so companies must address the return on investment.

Government regulations also play a major role for any operation in an organization. The cost of taxes, packaging and transportation norms, security, safety, and technology rights regulations are just some of the regulations organizations consider.

This study contributes to increasing the knowledge of government regulation impact on technology adoption by describing and specifying the relationship between these four factors. For instance, auto-ID or other technology implementations may be biased toward government influence. At the same time, the government's role is to facilitate industry growth. Therefore, assessing the optimal amount of government intervention is critical for a balance between a thriving industry and state order.

The other two most important factors, cost and quality, are measures to evaluate the adequate level of technology and government regulation investments.

After developing the mathematical model, this study tested its performance using data retrieved from a German carrier.

2 Methodology

The model was developed and tested following three steps:

1. User acceptance and requirements analysis survey: surveys were conducted in collaboration with selected northern European companies. In addition to their individual requirements for operation, their insights on current factors, obstacles, and facilitators were captured. These factors influence the extensive use of auto-ID technologies in the supply chain and are also relevant for technology adoption.
2. Development of the optimal model: a quantitative model to optimize values of relevant drivers or factors found in the industry survey was constructed. Two of the top factors were used as measures to evaluate the level of the other two factors. Based on these factors and their role in the model, the model was developed under four perspectives:

   - Technology adoption cost-oriented model: assesses the optimal technology investment level using cost as the evaluating variable (in terms of coefficients).
   - Technology adoption quality-oriented model: assesses the optimal technology investment level using quality as the evaluating variable (in terms of coefficients).
   - Government regulation cost-oriented model: assesses the optimal government investment level using cost as the evaluating variable (in terms of coefficients).
   - Government regulation quality-oriented model: assesses the optimal government investment level using quality as the evaluating variable (in terms of coefficients).

   The model measures technology adoption and government regulations as investments in monetary units. The rationale behind this approach is that both technology adoption and government regulations require some level of investment by organizations. For instance, technology adoption requires investment to purchase or develop and implement the technology. In addition, government regulations require companies to invest in specific equipment, control systems, audits, or other tasks or assets to comply with such regulations.

3. Testing: real data were retrieved from a private company in Germany to feed the model and develop results scenarios.

3 Literature review

Atkin et al. [4] posed a question deemed key to understanding the process of economic development and growth: "Why is adoption so slow for so many technologies?" A possible answer to this question is suggested in the same study: "It is rare to be able to observe firm's technology use directly, and rarer still to have direct measures of the costs and benefits of adoption." The study found that one of the firms that adopted technology belonged to a group that was not expected to be adopting such technology; coincidently, the unexpected adopting firm was also one of the firms that invested more in the technology. Apart from Atkin et al. [4], the literature has few studies addressing technology investment, and even fewer studies focusing on the "…measures of the costs and benefits of adoption." Dewan et al. [12] deemed the investment in information technology (IT) as risky because of "…the uncertainty about their economic impact." Specifically, the study aimed at assessing the impact on the required rate of return, firm's productivity, and market value. Devaraj and Kohli [11] decoupled technology investment and technology usage. Although the authors claimed the main driver of IT impact is usage rather than investment, the study never measured the difference between the two. Ultimately, Devaraj and Kohli [11] found a positive relationship between technology usage, revenue, and quality performance measures.

The literature contains different models for the assessment of the investment in IT. Gunasekaran et al. [14] present a conceptual model for the evaluation of the investment in IT. The model emphasizes evaluating the benefits of strategic, tactic, operational, financial, and intangible investment appraisal techniques, which delivers an integrative approach but does not provide a quantitative tool for the assessment. Doerr et al. [13] conducted an analysis of the costs and benefits of using radio frequency identification (RFID)/microelectromechanical systems technology. The authors' valuation approach combined a multicriteria tool for the evaluation of qualitative factors with the distinct feature of a Monte Carlo simulation of anticipated financial factors. Lu et al. [18] also evaluated the adoption of RFID technology. The authors developed an evaluation framework that uses a hybrid multiple criteria decision-making method. None of these studies included optimization.

Chen et al. [8] developed a nonlinear programming model to evaluate the impact of IT on multiple stages of the business operation based on data envelopment analysis (DEA), which can be used to assess investment justification. In a similar way, Azadeh et al. [5] used DEA for cost assessment. Their model first defines the hierarchy of the input/output criteria of the IT/information system (IS) investment through Delphi; then the model assigns weights to these criteria by using the voting analytic hierarchy process. Based on these input/output weighted indicators, the model defines investment alternatives, again with Delphi, and finally evaluates the efficient and inefficient IT/IS alternatives by means of DEA.

You et al. [24] introduced a method for evaluating enterprise resource management system investments based on the real option theory and a fuzzy payoff approach. The method, aimed at small and medium-sized enterprises because of its simplicity, uses active management in dealing with uncertainties to minimize the risk of failure. This approach is very similar to the one used by Zandi and Tavana [25], whose method also uses real option analysis to prioritize different IT investment strategies and then apply a fuzzy hierarchy process to quantify the risks of each one. Kauffman et al. [16] proposed a new option-based stochastic valuation modeling approach for the selection of IT under uncertainty that incorporates a mean reversion process to capture cost and benefit flow variations over time.

Chou et al. [9] also employed a fuzzy approach when evaluating IT/IS investments, as did Rouhani et al. [23] in their model for assessment and selection of enterprise systems when ranking an organization's alternatives. Chuu [10] developed a fuzzy multiple-attributes group decision-making algorithm for the selection of RFID technology.

Bojanc et al. [7] described a model for an optimal security-technology investment evaluation and a decision-making process based on a quantitative security-risk analysis. Aside from considering the obvious expenses for the necessary features, the model also considers the threats in a financial manner, expressing them in terms of the monetary losses the company would suffer.

Similar to the current work, Marchet et al. [20] presented a model to assess the impacts of information and communication technologies (ICT) on logistic operations—freight transportation specifically in this case—and to support the decision making for their adoption. The methodology is divided into two steps:

1. Conducting interviews to determine the macro-activities for intermodal transportation and the purpose groups for several ICT applications from which technology scenarios were derived.
2. Developing the model used to assess the costs and benefits for the proposed scenarios based on the activity-based costing methodology.

The model presented in this paper is based on the model introduced by Lee and Lee [17], namely the supply chain RFID investment evaluation model. The authors focused on giving decision makers insights into the investment needed for the adoption of RFID technology. The model presented in this paper has substantial differences from and contributions to previous work. Firstly, this study uses an empirical approach as a basis to select the most relevant variables for investment decision making of technology adoption. Consequently, this study delivers a broader model scope that includes technology adoption in general and government regulation as optimizing variables. The assessment of government regulations and the attempt to optimize their benefits are practically absent in operations literature. In addition, this work presents an evaluation of the model with real data.

The model developed in this paper also takes into consideration the work of Billington [6], who extends the economic order quantity formulation and proposes exponential parameters. However, the model presented in this study uses these exponential parameters in different directions dictated by the nature of the optimizing variables: technology investment and government regulations.

In regard to the influence of government regulations, Zhu et al. [26] analyzed the regulatory environment as one of the factors for e-business assimilation. Their findings confirm the importance of regulatory environments in this type of technology innovation adoption. Similarly, Adjerid et al. [2] looked at the impact of regulations on technology innovation. Specifically, the authors analyzed privacy regulation impacts on information exchanges in the health care industry. Results from Adjerid et al. [2] suggest that regulation impacts may be negative but also positive to operations under certain conditions. Luftman and Kempaiah [19] conducted a survey of IT executives of companies contributing to the Society of Information Management. The survey addressed key IT issues faced by enterprises; survey respondents ranked government regulation issues among the top 15 IT management concerns. Menon and Lee [21] also assessed the influence of government regulations in their study of IT investments in the health care industry. In their research, the authors examined the cost behavior of hospitals before and after a major regulation implementation; they found that while IT investments rose, improvement occurred in cost containment. Hwang et al. [15] encountered similar findings. The authors analyzed the adoption of data warehouse technology in Taiwan's banking industry and concluded that the government's actions, relaxing restrictions on industry's limits for new banks, had a major influence on technology adoption due to increased competition.

Newell et al. [22] tested Hick's induced innovation hypothesis and expanded upon the hypothesis with the inclusion of the influence of government regulations. Specifically, the study evaluated whether government regulations affected energy-efficiency innovation. The authors found government regulations did affect technology innovation in terms of energy efficiency in air conditioning and water heater companies.

This study acknowledges the scarce number of references related to the effects of government regulations. Nevertheless, the author believes that the lack of literature on this subject does not undermine its importance but rather offers a research niche. Any experienced operational and investment planner knows that planning without considering government regulations will cause substantial problems. The importance of government regulations is also supported by the industry survey presented in this research.

4 Industry survey

The industry survey explored user acceptance and user requirements for technology implementation to achieve end-to-end supply chain visibility. Three basic types of questions were asked:

- Multiple-choice questions with an option to add an open response, in the following form: "What would be a reason to implement…"
- Multiple-choice questions with an option to add an open response, in the following form: "What would keep you from implementing…"
- A multiple choice (Likert scale) request: "Please provide your level of enthusiasm regarding…" with five possible answers: high resistance, some resistance, neutral, moderately enthusiastic, or very enthusiastic.

The survey had 1333 individual registries allocated to each factor or driver. The responses identified which of these drivers were most relevant in the implementation decision process.

5 Optimal model

Based on the four relevant factors found in the survey, a mathematical model was developed. The model aims to optimize technology adoption investment and government regulation investment, as previously defined, based on quality and cost efficiencies.

5.1 Variables

The model uses the following variables:

- O = fixed-order cost per order cycle, $0 \leq O$.
- D = annual demand, $0 \leq D$.
- H = annual inventory holding cost per unit, $0 \leq \mathrm{H}$.
- C = operating cost per unit, $0 \leq C$.

- $R =$ order efficiency coefficient, $0 \le R \le 1$.
- $I =$ just-in-time (JIT) efficiency coefficient, $0 \le I \le 1$.
- $J =$ operating efficiency coefficient, $0 \le J \le 1$.
- $T =$ technology adoption level, $0 \le T$.
- $G =$ government regulation level, $0 < G$.
- $M =$ lowest ordering efficiency coefficient (R) level, $0 \le M < 1$.
- $N =$ highest ordering efficiency coefficient (R) level, $0 < N \le 1$ or $M < N \le 1$.
- $L =$ lowest JIT efficiency coefficient (I) level, $0 \le L < 1$.
- $U =$ highest JIT efficiency coefficient (I) level, $0 < U \le 1$ or $L < U \le 1$.
- $A =$ lowest operating efficiency coefficient (J) level, $0 \le A < 1$.
- $E =$ highest operating efficiency coefficient (J) level, $0 < E \le 1$ or $A < E \le 1$.
- $\beta_1 =$ technology exponential parameter for R, $0 \le \beta_1$.
- $\beta_2 =$ government exponential parameter for R, $0 \le \beta_2$.
- $\beta_3 =$ technology exponential parameter for I, $0 \le \beta_3$.
- $\beta_4 =$ government exponential parameter for I, $0 \le \beta_4$.
- $\beta_5 =$ technology exponential parameter for J, $0 \le \beta_5$.
- $\beta_6 =$ government exponential parameter for J, $0 \le \beta_6$.

5.2 Assumptions

The model uses the following assumptions:

- The fixed-order cost is set at the beginning of each periodic order cycle.
- The total demand level is known and constant.
- Technology adoption (investment) increases *R*, *I*, and *J* efficiency coefficients.
- Government regulations (cost) decrease *R*, *I*, and *J* efficiency coefficients.

5.3 Model

Based on the supply chain RFID investment evaluation model [17], the following is defined:

$$\text{Total Cost (TC)} = \frac{\mathrm{ORD}}{\mathrm{Q}} + \frac{\mathrm{IHQ}}{2} + \mathrm{JCD} + \mathrm{T} + \mathrm{G} \quad (1)$$

Equation 1 represents the total cost over the planning period. This equation extends the EOQ model by including ordering, JIT and operating efficiencies (R, I and J); and by considering technology and government regulation costs (T and G). Specifically, the first term represents the total order cost during the planning period, formed by the fixed-order cost (O), annual demand (D), order quantity (Q) and the order efficiency coefficient (R). This term shows that total cost change by the amount of orders placed, which in turn is influenced by the efficiency coefficient. The second term describes the inventory holding cost, and is made of the JIT coefficient (I), unit annual holding cost (H) and order quantity (Q). This term uses the average inventory levels during the period, and holding cost per unit—which in turn are influenced by the JIT efficiency coefficient, as variables for total cost change. The third term shows the total operating costs, based on the unitary costs (C) times annual demand (D), influenced by the operating efficiency (J). Fourth and fifth terms are technology and government regulation adoption costs, represented by T and G respectively.

$$\text{Optimal Order Quantity} = \mathrm{Q}^* = \sqrt{\frac{2\mathrm{ORD}}{\mathrm{HI}}} \quad (2)$$

5.3.1 Technology adoption optimization

Efficiency coefficients are defined as base e exponential functions, based on Billington [6]:

$$\mathrm{R} = (\mathrm{N} - \mathrm{M}) + (\mathrm{M} - \mathrm{N})e^{\beta_1 \mathrm{T}} \quad (3)$$

$$\mathrm{I} = (\mathrm{U} - \mathrm{L}) + (\mathrm{L} - \mathrm{U})e^{\beta_3 \mathrm{T}} \quad (4)$$

$$\mathrm{J} = (\mathrm{E} - \mathrm{A}) + (\mathrm{A} - \mathrm{E})e^{\beta_5 \mathrm{T}} \quad (5)$$

Conceptually, ordering efficiency (R) is defined as the degree to which the fixed-order cost per order cycle is reduced by technology adoption (investment). Similarly, JIT efficiency (I) is defined as the degree to which the time gap between the point of delivery and the time of consumption/production is reduced by technology adoption (investment). Operating efficiency (J) is defined as the degree to which the operating cost per unit is reduced by technology adoption (investment). There are several ways in which technology may improve R, I and J. Specifically, the essence of Auto-ID technologies is an increased visibility through an enhanced data capturing, transmission and processing. Better data transmission may lower fixed-order costs (R) because it would deem physical shipping of—order—documents unnecessary, and increase accuracy of order placement. This same information sharing may improve reaction times of operating activities involved in product delivery, which in turn will shorten the time window between order placement and order delivery (I). Similarly, information on where delivering assets are, accuracy on inventory, product in transit and demand behavior will significantly improve operating efficiency (J), and consequently reducing operation costs.

R, I, and J are defined as the degree to which fixed-order cost, time gap, and operating cost decrease. In other words, the higher the degree, the higher *the decrease rate* of fixed-order cost, time gap, and operating cost. When R, I, and J increase, the more fixed-order cost, time gap, and operating cost decrease.

From these definitions, ordering efficiency (TC first term) and operating efficiency (TC third term) are cost oriented, while JIT efficiency (TC second term) addresses quality (i.e., service).

5.3.1.1 Technology adoption cost-oriented model The technology adoption cost-oriented optimization model is reduced to:

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

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

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

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

After obtaining the first order condition (FOC) with respect to T and performing algebraic operations, R* and T* optimal equations are obtained (The "Appendix" provides the complete development of the model, equations' numbers are in sequence with those of the "Appendix"):

$$R^* = \left[\frac{-\beta_1(M-N)e^{\beta_1 T}}{1 + CD(\beta_5(A-E)e^{\beta_5 T})}\right]^2 \frac{ODHI}{2} \tag{14}$$

$$T^* = \frac{\ln\left(\frac{R^*-N+M}{M-N}\right)}{\beta_1} \tag{15}$$

5.3.1.2 Technology adoption quality-oriented model The technology adoption quality-oriented optimization model is:

$$TC_Q = \frac{IHQ}{2} + T \tag{16}$$

$$TC_Q = g(T) \tag{17}$$

$$I = i(T) \tag{18}$$

Following the same process, *I** and *J** optimal equations are obtained:

$$I^* = \frac{ORDH\left[\beta_3(L-U)e^{\beta_3 T}\right]^2}{2} \tag{23}$$

$$J^* = (E-A) + (A-E)e^{\beta_5 T^*} \tag{24}$$

5.3.2 Government regulation optimization

The government regulation efficiency coefficients are also defined as base *e* exponential functions, based on Billington [6]:

$$R = (N-M) + (N-M)e^{\frac{1}{\beta_2 G}} \tag{25}$$

$$I = (U-L) + (U-L)e^{\frac{1}{\beta_4 G}} \tag{26}$$

$$J = (E-A) + (E-A)e^{\frac{1}{\beta_6 G}} \tag{27}$$

Ordering efficiency (R) is now defined as the degree to which the fixed-order cost per order cycle is *increased by government regulations (investment).* Similarly, JIT efficiency (I) is defined as the degree to which the time gap between the point of delivery and the time of consumption/production is *increased by government regulations (investment).* Operating efficiency (J) is defined as the degree to which the operating cost per unit is *increased by government regulations (investment).*

Unlike the technology adoption model, R, I and J are now defined as the degree to which fixed-order cost, time gap, and operating cost *increase*. In other words, the higher the degree, the higher *the increase rate* of fixed-order cost, time gap, and operating cost. When R, I, and J increase, the more fixed-order cost, time gap, and operating cost increase.

5.3.2.1 Government regulation cost-oriented model The government regulation cost-oriented optimization model is reduced to:

$$TC_c = \frac{ORD}{Q} + JCD + G \tag{28}$$

$$TC_c = f(G) \tag{29}$$

$$R = r(G) \tag{30}$$

$$J = j(G) \tag{31}$$

After obtaining the FOC with respect to *G* and performing algebraic operations, *R** and *G** optimal equations are obtained (The "Appendix" provides the complete development of the model, equations' numbers are in sequence with those of the "Appendix"):

$$R^* = \frac{\left[(N-M)e^{\frac{1}{\beta_2 G}}\right]^2 ODHI}{2\left[\beta_2 G\left(1 - CD\left(\frac{(E-A)e^{\frac{1}{\beta_6 G}}}{\beta_6 G^2}\right)\right)\right]^2} \tag{36}$$

$$G^* = \frac{1}{\beta_2 \ln\left(\frac{R^*-N+M}{(N-M)}\right)} \tag{37}$$

5.3.2.2 Government regulation quality-oriented model The government regulation quality-oriented optimization model is:

$$TC_Q = \frac{IHQ}{2} + G \tag{38}$$

$$TC_Q = g(G) \tag{39}$$

$$I = i(G) \tag{40}$$

Following the same process, I^* and J^* optimal equations are obtained:

$$I^* = \frac{ORDH\left[(U-L)e^{\frac{1}{\beta_4 G}}\right]^2}{2\left[\beta_4 G^2\right]^2} \tag{45}$$

$$J^* = (E-A) + (E-A)e^{\frac{1}{\beta_6 G^*}} \tag{46}$$

6 Testing

To test the model, data from a German container consignee company was retrieved. These data are for 2008 through 2015 and include dates, times, costs, operation type, and currency information. For confidentiality, containers were assigned a random number to enable data sorting while preventing direct container identification. This data set provided information on the following variables[1]:

- Fixed-order cost per order cycle.
- Annual demand.
- Annual inventory holding cost per unit.
- Operating cost per unit.

Based on these data, Table 1 presents the calculated values for the model variables, coefficients, and exponential parameters.

Based on annual demand, annual inventory holding, and operating cost per unit, the total annual operating result is USD $3,802,027.19. Taking this operating total cost as a basis, an investment threshold was established for both the technology adoption and government regulation optimization. Such a threshold assumes that technology adoption and government regulation investments would not make sense if they each represent more than 10% of the total operating cost. Although this limit is arbitrary, it is also flexible and could be easily changed in further testing.

6.1 Technology adoption testing

Using the 10% limit of total operating cost, the model calculated optimal R, I, and J (Table 2).

The way the efficiency coefficients in technology adoption are defined means that the higher value such coefficients hold, the larger the reduction in cost and time gap. Specifically, the higher the value of ordering efficiency (R), the larger the reduction in fixed-order cost per order cycle. The higher the value of JIT efficiency (I), the larger the reduction in the time gap between the point of delivery and the time of consumption/production—and thus a higher quality or service. The higher the value of operating efficiency (J), the larger the reduction in the operating cost per unit. In short, the higher any of these coefficient values are, the higher the benefit drawn from technology adoption (or investment).

Figures 1, 2, and 3 depict the behavior of the ordering (R), JIT (I), and operating efficiency (J) coefficients, respectively, based on the data provided by the northern European companies.

These figures show concave curves for the cost-oriented optimization—ordering (R) and operating efficiency (J)—and a convex pattern for the quality-oriented efficiency coefficient—JIT (I). However, the three coefficients show the expected increase with increasing technology adoption (or investment). This means more benefits in cost and quality—that is, higher rates of cost and delivery-consumption time gap reduction—by increasing technology adoption.

Nevertheless, ordering (R) and operating efficiency (J) show asymptotic curves, at least within this scale. This could be due to diminishing return effects making efficiencies stall at a certain level of technology adoption. In the test of ordering (R) and operating efficiency (J), their curves become practically flat at 6%, while JIT (I) presents the opposite effect, starting an exponential increase precisely at 6%. This overall behavior suggests a shift in the benefits, relaying early cost benefits to delayed quality benefits in the technology investment scale. The practical perspective is that reducing the time gap (J), requires more investment in technology than reducing fixed-order and operating costs. However, once the reduction on this time gap starts, it delivers exponential benefits.

The model output is beneficial to the company because it indicates the optimal investment level. For instance, the shift point of 6% represents the threshold the organization (whose data the analysis is based on) needs to consider, depending on the type of benefits—costs against quality—it is seeking. Should these benefits be of a cost nature, then 6% is the amount of technology adoption or investment the company needs to achieve to maximize cost benefits. On the other hand, if the benefits the company seeks to maximize are of a quality or service nature, then the amount of technology adoption or investment the company needs to make is 10%. If the company likes to maximize all benefits—cost and quality—the amount of technology investment remains at 10% of the total annual operating cost for this case.

6.2 Government regulation testing

In the government regulation model test, the same 1–10% scale of total operating cost was used. Table 3 shows optimal R, I, and J for government regulation.

[1] Input values for efficiency coefficients and exponential parameters were taken from previous modeling experiences.

Table 1 Values for the model variables, coefficients, and exponential parameters

Variable	Description	Value
O	Fixed-order cost per order cycle	USD 75.50
D	Annual demand (trips)	11,200.00
H	Annual inventory holding cost per unit	USD 81.48
C	Operating cost per unit	USD 257.99
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
β_1	Technology exponential parameter for R	0.00002
β_2	Government exponential parameter for R	− 0.00002
β_3	Technology exponential parameter for I	0.00001
β_4	Government exponential parameter for I	− 0.00001
β_5	Technology exponential parameter for J	0.00002
β_6	Government exponential parameter for J	− 0.00002

Table 2 Optimal values of R, I, and J for technology adoption

T (%)	R^*	I^*	J^*
1	3.92E−06	1.847E−08	2.797E−06
2	3.98E−06	4.018E−08	2.845E−06
3	4.01E−06	8.665E−08	2.868E−06
4	4.03E−06	1.860E−07	2.879E−06
5	4.04E−06	3.987E−07	2.884E−06
6	4.04E−06	8.535E−07	2.886E−06
7	4.04E−06	1.827E−06	2.887E−06
8	4.04E−06	3.908E−06	2.888E−06
9	4.04E−06	8.360E−06	2.888E−06
10	4.04E−06	1.788E−05	2.888E−06

The investments companies make for government regulation compliance are often perceived as a burden with negative effects on efficiency and costs. Therefore, in the case of government regulation, the direction of the effects of the efficiency coefficient are inverted when compared to the effect of technology investment. The government regulations coefficient definitions establish that the higher the coefficient's value, the larger the increase in cost and time gap. More specifically, the higher the value of ordering efficiency (R), the larger the increase in fixed-order cost per order cycle. The higher the value of JIT efficiency (I), the larger the increase in the time gap between the point of delivery and the time of consumption/production—and thus a lower quality or service. The higher the value of operating efficiency (J), the larger the increase in the operating cost per unit. In short, the higher any of these coefficient values are, the higher the negative impact (i.e., the lower the benefit from government regulations [or investment]).

Figures 4, 5, and 6 depict the behavior of the ordering (R), JIT (I), and operating efficiency (J) coefficients, respectively, based on the data provided by the northern European companies.

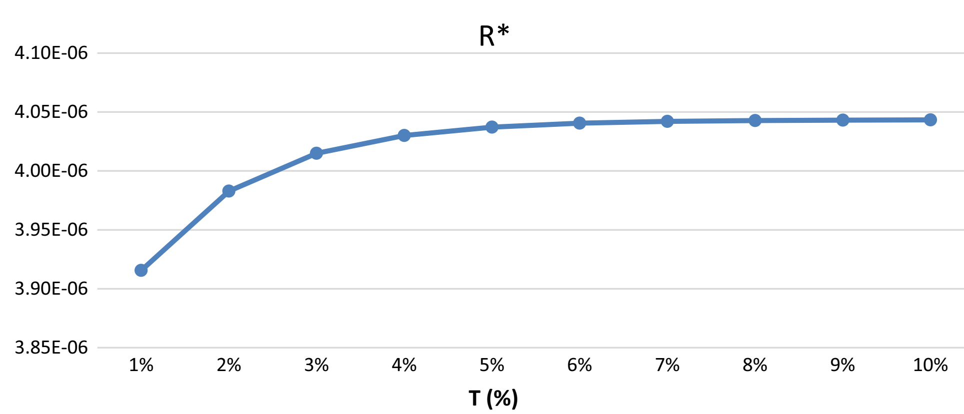

Fig. 1 Order efficiency coefficient behavior for technology adoption optimization

Fig. 2 JIT efficiency coefficient behavior for technology adoption optimization

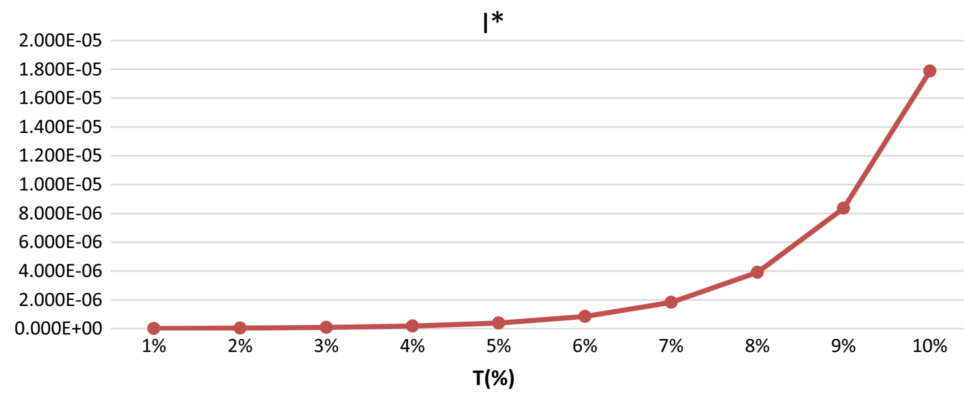

Fig. 3 Operating efficiency coefficient behavior for technology adoption optimization

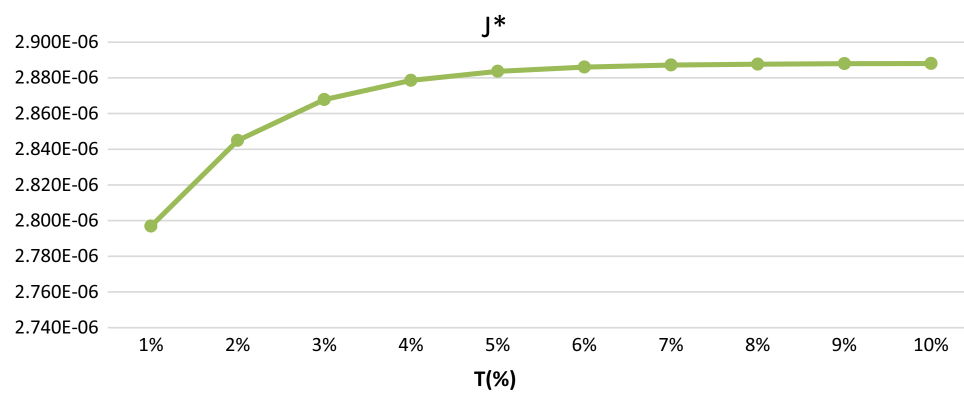

Table 3 Optimal values of R, I, and J for government regulation

G (%)	*R**	*I**	*J**
1	5.062E+03	2.740E−04	3.616E+03
2	1.754E+04	2.376E−04	1.253E+04
3	3.215E+04	1.128E−04	2.296E+04
4	4.480E+04	5.532E−05	3.200E+04
5	5.362E+04	2.948E−05	3.830E+04
6	5.848E+04	1.694E−05	4.177E+04
7	6.009E+04	1.036E−05	4.292E+04
8	5.940E+04	6.673E−06	4.243E+04
9	5.724E+04	4.482E−06	4.089E+04
10	5.425E+04	3.117E−06	3.875E+04

These figures show that cost-oriented coefficients—ordering efficiency (R) and operating efficiency (J)—increase as government regulation expenses increase. This is expected due to the negative impacts of government regulation on efficiency and cost, which was discussed previously. However, it is counterintuitive to see that both coefficients decrease after a 7% government regulation investment. This behavior is more evident in the quality-oriented part of the model, namely the JIT efficiency (I) coefficient, which shows a decreasing curve for increasing levels of government regulation. There could be several reasons for these behaviors, ranging from practical causes to mathematical construction. A practical cause could be that for these specific data and setup, government regulation effects shift from affecting fixed-order cost to impact some other type of costs not captured by the input value of operating cost per unit; therefore, ordering efficiency (R) and operating efficiency (J) decrease after a certain level. Another reason could be that the chosen exponential parameters are not entirely accurate for representing the effect on cost and quality. Further research focused on assessing this latter reason still needs to be performed.

7 Conclusions and further research

This study provides an optimization model based on factors (i.e., drivers) found relevant for practitioners: quality, cost, technology adoption or use, and government regulations. The contribution of this paper is three-fold:

- It supports the relevance of these factors with field data collected from northern European companies.
- It delivers an optimization model that indicates optimal levels of technology and government regulation investments for maximizing cost and quality benefits.

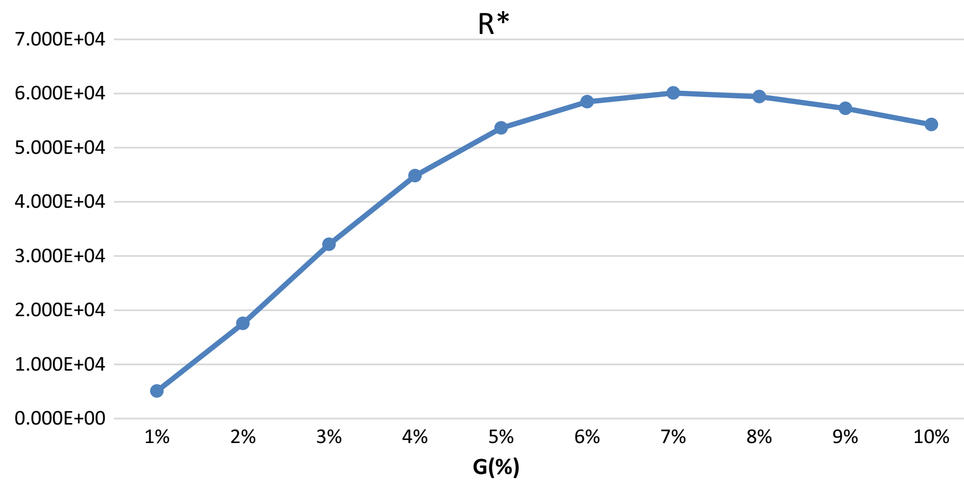

Fig. 4 Order efficiency coefficient behavior for government regulation optimization

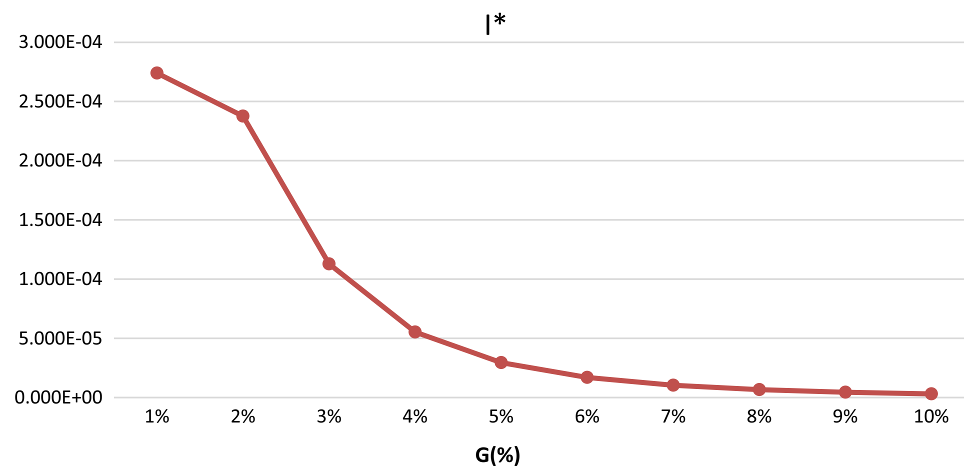

Fig. 5 JIT efficiency coefficient behavior for government regulation optimization

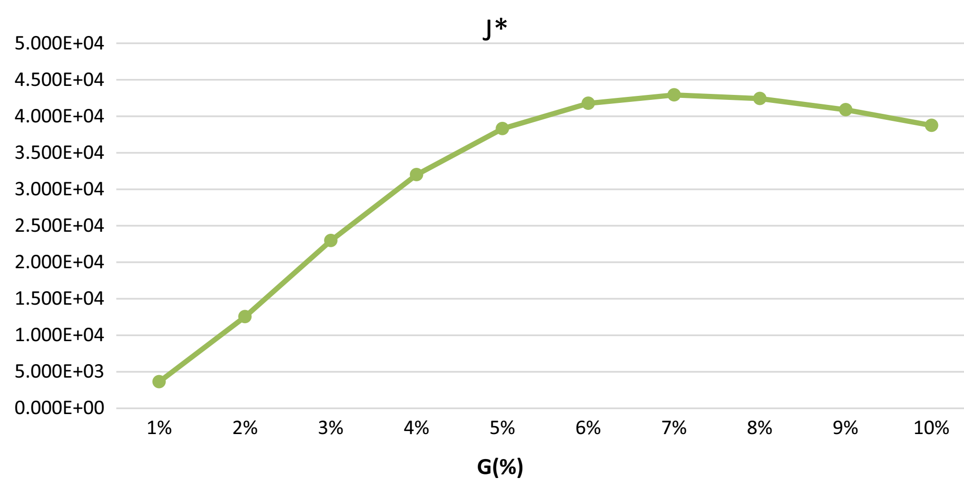

Fig. 6 Operating efficiency coefficient behavior for government regulation optimization

- It tests the model with real data retrieved from a German carrier.

Results confirm that the model provides a theory-consistent outcome for technology investment for both efficiencies: cost and quality. However, government regulation testing shows a counterintuitive behavior at higher levels of investment for the cost-oriented coefficients, and at all levels of investment for the quality-oriented coefficient. Data limitations prevent confirming the reasons for these patterns. Nevertheless, practical and modeling experiences suggest these reasons could be government regulation effects shifting to costs not captured by the input values of the data, or chosen exponential parameters not representing the total effect on cost and quality. Also, this could help explain to some extent the regulation duality found in Adjerid et al. [2], by arguing that these cost shifts could pertain to changing conditions, such as the ones presented by Adjerid et al. [2].

Further research should focus on assessing the robustness of the model against values not captured and the data completeness requirements of the model. Additionally, exponential parameters should be confirmed through further testing with different data sets. A further, more sophisticated analysis is envisioned considering multiple-variable simultaneous optimization. The need for this analysis is supported by the fact that, generally, organizations must make investment decisions considering the simultaneous effects of competing or conflicting factors. Therefore, optimization based on simultaneous variables would be closer to reality.

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Appendix

Technology adoption cost-oriented model

The derivative of TC_c with respect to technology (T) is given by:

$$\frac{\partial(\mathrm{TC_c})}{\partial \mathrm{T}} = \frac{\mathrm{O}\left(\frac{\partial R}{\partial T}\right)\mathrm{D}}{\mathrm{Q}} + \frac{\partial \mathrm{J}}{\partial \mathrm{T}}\mathrm{CD} + 1 \tag{10}$$

From Eqs. 3 and 8:

$$\frac{\partial \mathrm{R}}{\partial \mathrm{T}} = \beta_1(\mathrm{M}-\mathrm{N})e^{\beta_1 \mathrm{T}} \tag{11}$$

From Eqs. 10 and 7, setting Eq. 10 $= 0$:

$$\frac{\partial \mathrm{R}}{\partial \mathrm{T}} = -\left(\frac{1+\mathrm{CD}\left(\frac{\partial J}{\partial T}\right)}{\mathrm{OD}}\right)\mathrm{Q} \tag{12}$$

Given that:

$$\frac{\partial \mathrm{J}}{\partial \mathrm{T}} = \beta_5(\mathrm{A}-\mathrm{E})e^{\beta_5 \mathrm{T}}$$

Then from Eqs. 11 and 12:

$$\beta_1(\mathrm{M}-\mathrm{N})e^{\beta_1 \mathrm{T}} = -\left(\frac{1+\mathrm{CD}\left(\beta_5(\mathrm{A}-\mathrm{E})e^{\beta_5 \mathrm{T}}\right)}{\mathrm{OD}}\right)\mathrm{Q} \tag{13}$$

Substituting Eq. 2 in Eq. 13's Q and solving for R^*:

$$\mathrm{R}^* = \left[\frac{-\beta_1(\mathrm{M}-\mathrm{N})e^{\beta_1 \mathrm{T}}}{1+\mathrm{CD}(\beta_5(\mathrm{A}-\mathrm{E})e^{\beta_5 \mathrm{T}})}\right]^2 \frac{\mathrm{ODHI}}{2} \tag{14}$$

From Eqs. 3 and 14:

$$\mathrm{T}^* = \frac{\ln\left(\frac{\mathrm{R}^*-\mathrm{N}+\mathrm{M}}{\mathrm{M}-\mathrm{N}}\right)}{\beta_1} \tag{15}$$

Technology adoption quality-oriented model

Following the same process, from Eqs. 16 and 17:

$$\frac{\partial \mathrm{TC_Q}}{\partial \mathrm{T}} = 1 + \frac{\mathrm{HQ}\left(\frac{\partial I}{\partial T}\right)}{2} \tag{19}$$

Setting Eq. 20 $= 0$

$$\frac{\partial \mathrm{I}}{\partial \mathrm{T}} = -\frac{2}{\mathrm{HQ}} \tag{20}$$

From Eqs. 4 and 18:

$$\frac{\partial \mathrm{I}}{\partial \mathrm{T}} = \beta_3(\mathrm{L}-\mathrm{U})e^{\beta_3 \mathrm{T}} \tag{21}$$

Then:

$$\beta_3(\mathrm{L}-\mathrm{U})e^{\beta_3 \mathrm{T}} = -\frac{2}{\mathrm{HQ}} \tag{22}$$

Substituting Eq. 2 in Q:

$$\mathrm{I}^* = \frac{\mathrm{ORDH}\left[\beta_3(\mathrm{L}-\mathrm{U})e^{\beta_3 \mathrm{T}}\right]^2}{2} \tag{23}$$

J^* is obtained from Eqs. 5 and 15:

$$\mathrm{J}^* = (\mathrm{E}-\mathrm{A}) + (\mathrm{A}-\mathrm{E})e^{\beta_5 \mathrm{T}^*} \tag{24}$$

Summarizing, the following optimal equations were obtained:

$$\mathrm{R}^* = \left[\frac{-\beta_1(\mathrm{M}-\mathrm{N})e^{\beta_1 \mathrm{T}}}{1+\mathrm{CD}(\beta_5(\mathrm{A}-\mathrm{E})e^{\beta_5 \mathrm{T}})}\right]^2 \frac{\mathrm{ODHI}}{2} \tag{14}$$

$$\mathrm{T}^* = \frac{\ln\left(\frac{\mathrm{R}^*-\mathrm{N}+\mathrm{M}}{(\mathrm{M}-\mathrm{N})}\right)}{\beta_1} \tag{15}$$

$$\mathrm{I}^* = \frac{\mathrm{ORDH}\left[\beta_3(\mathrm{L}-\mathrm{U})e^{\beta_3 \mathrm{T}}\right]^2}{2} \tag{23}$$

$$\mathrm{J}^* = (\mathrm{E}-\mathrm{A}) + (\mathrm{A}-\mathrm{E})e^{\beta_5 \mathrm{T}^*} \tag{24}$$

Government regulation optimization

The derivative of TC_c with respect to government regulations (G) is given by:

$$\frac{\partial(\mathrm{TC_c})}{\partial \mathrm{G}} = \frac{\mathrm{O}\left(\frac{\partial R}{\partial G}\right)\mathrm{D}}{\mathrm{Q}} + \frac{\partial \mathrm{J}}{\partial \mathrm{G}}\mathrm{CD} + 1 \tag{32}$$

From Eqs. 26 and 31:

$$\frac{\partial R}{\partial G} = -\frac{(N-M)e^{\frac{1}{\beta_2 G}}}{\beta_2 G^2} \tag{33}$$

From Eqs. 33 and 30, setting Eq. 33 $= 0$:

$$\frac{\partial R}{\partial G} = -\left(\frac{1 + CD\left(\frac{\partial J}{\partial G}\right)}{OD}\right)Q \tag{34}$$

Then, from Eqs. 33 and 34:

$$\frac{(N-M)e^{\frac{1}{\beta_2 G}}}{\beta_2 G^2} = \left(\frac{1 + CD\left(\frac{\partial J}{\partial G}\right)}{OD}\right)Q \tag{35}$$

Substituting Eq. 2 in Eq. 35's Q and solving for R^*:

$$R^* = \frac{\left[(N-M)e^{\frac{1}{\beta_2 G}}\right]^2 ODHI}{2\left[\beta_2 G\left(1 - CD\left(\frac{(E-A)e^{\frac{1}{\beta_6 G}}}{\beta_6 G^2}\right)\right)\right]^2} \tag{36}$$

From Eq. 26:

$$G^* = \frac{1}{\beta_2 \ln\left(\frac{R^*-N+M}{(N-M)}\right)} \tag{37}$$

Government regulation quality-oriented model

Following the same process, from Eqs. 39 and 40:

$$\frac{\partial TC_Q}{\partial G} = 1 + \frac{HQ\left(\frac{\partial I}{\partial G}\right)}{2} \tag{41}$$

Setting Eq. 41 $= 0$:

$$\frac{\partial I}{\partial G} = -\frac{2}{HQ} \tag{42}$$

From Eqs. 27 and 41:

$$\frac{\partial I}{\partial G} = -\frac{(U-L)e^{\frac{1}{\beta_4 G}}}{\beta_4 G^2} \tag{43}$$

Then:

$$-\frac{(U-L)e^{\frac{1}{\beta_4 G}}}{\beta_4 G^2} = -\frac{2}{HQ} \tag{44}$$

Substituting Eq. 2 in Eq. 44's Q:

$$I^* = \frac{ORDH\left[(U-L)e^{\frac{1}{\beta_4 G}}\right]^2}{2\left[\beta_4 G^2\right]^2} \tag{45}$$

J^* is obtained from Eqs. 28 and 38:

$$J^* = (E-A) + (E-A)e^{\frac{1}{\beta_6 G^*}} \tag{46}$$

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