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Incentive Mechanism for Quality Inspection: A Linear Programming Approach

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ABSTRACT

This study develops an incentive mechanism model for outsourced personnel in product quality inspection, based on a principal-agent relationship. The core challenge lies in misaligned incentives, where agents often prioritize output volume over quality. By integrating Mechanism Design Theory (MDT) and Linear Programming (LP), our model aligns the principal's objective of minimizing defective products with the agent's utility maximization, subject to Incentive Compatibility and Individual Rationality constraints. Our analysis reveals that the optimal incentive structure combines a basic wage with a performance-based bonus. The optimal effort level of outsourced personnel increases with both rising losses due to defective products and enhanced detection effort effectiveness. The model also shows that optimal inspection allocation should be assigned to personnel with higher capabilities, especially for high-risk products. This research provides a theoretical contribution by integrating MDT and LP for incentive design and offers practical implications for improving product quality through a measurable incentive framework.

Keywords: Incentive mechanism, outsourcing, quality checking, Mechanism design theory, Linear programming.

INTRODUCTION

In the fierce business competition, many companies adopt outsourcing strategies in an effort to improve operational efficiency and reduce production costs (Nyameboame & Haddud, 2017). Outsourcing has become a common practice in a variety of industries, from manufacturing to information technology (Vardhan et al., 2024). According to data from Grand View Research (2023), the growth of the outsourcing workforce in Indonesia shows a positive trend with a compound annual growth rate of around 10% during the 2021–2025 period ("Indonesia Business Process Outsourcing (BPO) Market Growth & Trends," 2023). However, behind the economic benefits offered, outsourcing brings challenges, especially in product quality control.

One of the main problems in outsourcing practices is how to ensure that outsourcing personnel have the right incentives to conduct careful and honest product quality checks.

This problem arises due to incentive misalignment between the company and outsourced personnel (Bhattacharya & Singh, 2019). On the one hand, companies want high-quality products to improve customer satisfaction and reduce warranty costs (Zhou et al., 2024). On the other hand, outsourced workers who are paid based on the number of products produced (piece-rate system) tend to prioritize quantity over quality, which can result in defective products passing through to customers (Friis et al., 2015).

The passing of defective products to customers has serious consequences for the company, namely decreased customer satisfaction, damage to brand reputation, increased warranty costs and handling of complaints, and potential loss of market share (Lucky & Takim, 2015). According to a study conducted by (Shipley et al., 2022), The cost of external failure due to defective products reaching customers is several times the cost of inspection and prevention. Therefore, designing an effective incentive mechanism to encourage outsourcing personnel to properly conduct quality checks is critical to business sustainability.

This problem can be analysed with Mechanism Design Theory (MDT), a branch of Economic Theory that focuses on designing interaction rules to achieve desired outcomes when agents have personal information and incentives that may not align with the goals of the mechanism designer (Börgers, 2015). In the context of outsourcing, the company acts as a principal who tries to encourage outsourcing agents to properly conduct quality checks, even though this action may conflict with their incentives to maximize output.

This study aims to develop an Incentive Mechanism Model for outsourcing personnel to be willing to perform product quality inspections correctly, to reduce the passing of defective products to customers. This model is developed based on the MDT concept and modeled with Linear Programming (LP). The LP model was chosen because it is structured and measurable, considers all relevant constraints, and can be mathematically proven to achieve the best solution. In this research, the relevant constraints are Incentive Compatibility (IC) and Individual Rationality (IR). The IC requirement ensures that outsourcing personnel have an incentive to act honestly in reporting quality inspection results, while IR ensures that outsourcing personnel are willing to participate in the mechanism (Ballen, 2023).

The main contribution of this research is the development of a comprehensive LP model to design optimal incentive mechanisms in the context of outsourcing, with a special focus on product quality inspection. This model considers the economic aspects of the principal-agent relationship and pays attention to the honesty factor of outsourcing as a key element in ensuring product quality. In addition, this research also provides practical insights for companies in designing outsourcing contracts to harmonize incentives between companies and outsourcing workers.

MDT focuses on designing interaction rules to achieve desired outcomes when agents have personal information and incentives that may not align with the goals of the mechanism designer. This theory was originally developed by several prominent economists, such as Leonid Hurwicz, Eric Maskin, and Roger Myerson, who were awarded the Nobel Prize in Economics in 2007 for their contributions to the development of this theory (Börgers, 2015). In contrast to classical game theory which analyzes how agents behave within pre-set rules, MDT focuses on designing optimal rules to achieve specific goals (Börgers, 2015). In this context, the principal designer seeks to design an incentive system that encourages agents to honestly disclose their personal information and act according to the principal's objectives, even though such actions may conflict with their incentives (Liang et al., 2023).

The key concepts in MDT are IC and IR (Börgers, 2015). ICs ensure agents have an incentive to act honestly and disclose their personal information accurately. IR ensures agents are willing to participate in the mechanism, by ensuring the expected utility of their participation is at least equal to the utility of their reservation. In its development, MDT has been applied in various contexts, including in auction issues, public resource allocation, and contract design. (Jiang & Ma, 2025) applies this theory in the context of the data market, using a multitasking principal-agent model to develop incentive mechanisms to optimize data circulation and security.

The principal-agent model is a theoretical framework that analyses the relationship between two parties, namely the principal (assignee) and agent (executor of the task). This model becomes relevant when the principal delegates tasks to the agent, but cannot fully observe the agent's actions or has less information than the agent. This situation creates information asymmetry that can result in two main problems, namely adverse selection (before the contract) and moral hazard (after the contract) (Tan et al., 2023).

Adverse selection occurs when agents have personal information about their characteristics (e.g., ability or productivity) that the principal did not know before the contract was made. Moral hazard occurs when the principal is unable to fully observe the agent's actions after the contract is made, so the agent may not act in the principal's best interests (Liang et al., 2023).

In the context of outsourcing, information asymmetry is a significant problem. (Zhang et al., 2022) have analysed how information asymmetry influences production outsourcing and quality management decisions. They compared two outsourcing structures, namely turnkey (contract manufacturers who buy components directly from suppliers) and buy-sell (original equipment manufacturers buy components from suppliers and resell them to contract manufacturers). Their results show that the optimal outsourcing structure depends on a variety of factors, including compensation, external failure costs, cost differences between suppliers, and the contract manufacturer's skill level.

(Tan et al., 2023) have developed a dynamic moral hazard model to derive optimal incentive mechanisms in the context of construction waste recycling. They used Bayesian learning to update the estimates of waste collectors' personal information. The results of their research show collectors are always motivated to voluntarily maintain a supply of high-quality waste in an optimal mechanism. In addition, personal information is gradually revealed through learning, which is conducive to controlling incentive costs.

Quality control is a significant challenge in the context of outsourcing, especially when outsourced workers are paid based on the number of products produced (Uluskan et al., 2016). In this situation, outsourcing personnel may face a trade-off between quantity and quality, which can result in the passage of defective products to customers if there is no proper incentive to properly conduct quality checks.

Several researchers have analysed how to design incentive mechanisms to encourage quality control in the context of outsourcing. (Zhang et al., 2022) examined how original equipment manufacturers can design contracts with contract manufacturers to encourage them to use quality components and/or adopt the right production processes to produce quality products. They found that optimal contract design depends on a variety of factors, including compensation, external failure costs, and cost differences between suppliers. (Liang et al., 2023) developed a quality incentive contract for the procurement of public technology innovations under asymmetrical information conditions. They found that under asymmetric information, the government can motivate companies to conduct independent selection and improve the quality of technological innovation by designing information filtering contracts.

In a more specific context of outsourcing labour, some researchers have analyzed how to design incentives to encourage honesty in quality checks (Zhang, 2024). However, research that specifically analyzes incentive mechanisms for outsourcing personnel in product quality inspection is still limited. This study aims to fill the gap by developing a comprehensive incentive mechanism model based on MDT and modelled with LP. LP is a Mathematical Optimization technique that aims to maximize or minimize the function of linear objectives by paying attention to linear constraints. This technique has been widely applied in a variety of contexts, due to its ability to handle optimization problems with many variables and constraints (Börgers, 2015).

In the context of incentive mechanism design, LP will be used to formulate optimization problems where principals seek to maximize the objective function (profit or social utility) by paying attention to constraints such as IC and IR. The LP formulation allows the principal to determine the optimal incentive structure that encourages the agent to act following the principal's objectives (Zhu et al., 2025).

Some studies apply the Optimization Model in the design of incentive mechanisms for several contexts. For example, (Jiang & Ma, 2025) used an optimization approach to develop incentive mechanisms in the data market, while (Tan et al., 2023) used an optimization model to obtain optimal incentive mechanisms in the context of waste recycling.

In this study, the LP model is used to formulate an optimization problem in which the company seeks to maximize profits by designing an incentive mechanism that encourages outsourced personnel to properly conduct quality checks. This LP model considers a variety of factors, including production costs, selling prices, losses due to defective products, and incentive structures for outsourced personnel.

Although several studies have analyzed incentive mechanisms in various contexts (Ihle et al., 2023), including outsourcing and quality control (He et al., 2024), there is still a gap in the literature regarding incentive mechanisms for outsourcing personnel in product quality inspection. In particular, research integrating MDT and LP to develop a comprehensive model that considers the honesty of outsourcing personnel is still limited.

This research aims to fill this gap by developing a model of an incentive mechanism with a comprehensive LP for outsourced personnel in product quality inspection. This model not only considers the economic aspects of the principal-agent relationship but also pays attention to the honesty factor of outsourcing personnel as a key element in ensuring product quality. In addition, this research also provides practical insights for companies in designing outsourcing contracts that can align incentives between companies and outsourcing personnel.

METHODS

This study develops a model of incentive mechanisms for outsourcing personnel in product quality inspection using the MDT and LP approaches (Figure 1). The conceptual framework of this research is based on the principal-agent relationship between the company (principal) and outsourced personnel (agent) (Bernhold & Wiesweg, 2021), where companies seek to design incentive mechanisms that encourage outsourced personnel to properly conduct quality checks, even though such actions may conflict with their incentives to maximize output.

In this model, companies face the problem of information asymmetry in two forms, namely adverse selection, the ability of outsourced personnel cannot be fully observed by the company, and moral hazard, the level of effort of outsourced personnel in quality checks that cannot be fully observed by the company. To address this issue, companies need to design incentive mechanisms that meet two main requirements: IC and IR (Börgers, 2015). IC ensures that outsourced personnel have the incentive to act honestly in reporting quality inspection results (Mohammadi & Hashemi Golpayegani, 2021). IR ensures outsourced personnel are willing to participate in the mechanism, by ensuring that the expected utility of participation is at least equal to their reservation utility (Sadiq & Ahmed, 2020). By observing these two requirements, the company strives to maximize profits by minimizing the number of defective products that pass to customers.

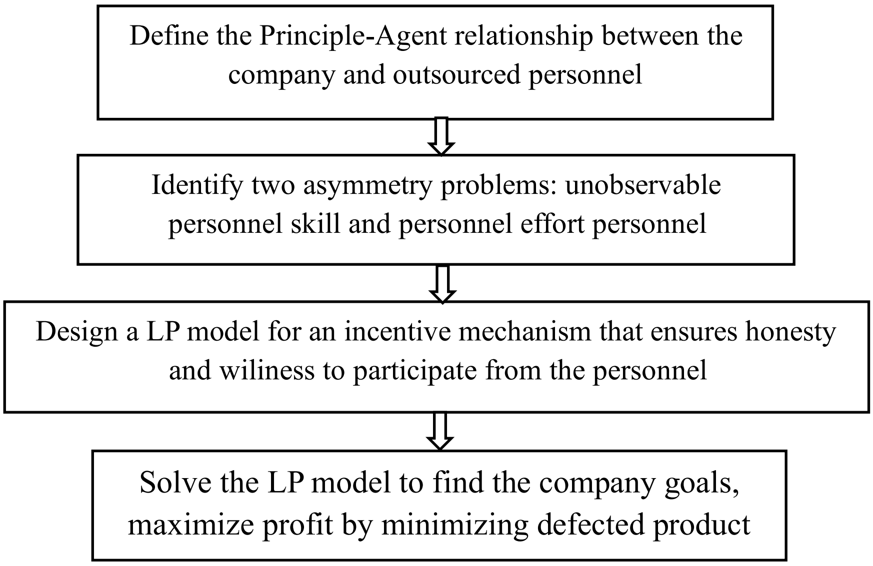

Figure 1. Research Methods: Development of Integration Model of MDT and LP
Source: Authors' work, 2025

The model developed in this study is a conceptual model, or mathematical model-based research. This study does not use empirical sampling; it simply develops and analyses a mathematical model, rather than generalizing findings from the sample to the population.

The model developed in this study is based on several assumptions. Outsourcing workers are initially rewarded based on the number of products produced (piece-rate system). The model develops additional incentive structures to encourage correct quality checks. Outsourcing personnel have different types of abilities in conducting quality checks (Daniel et al., 2018). This type of ability is the personal information of the outsourcing

personnel that cannot be fully observed by the company. Outsourcing personnel can choose the level of effort in conducting quality checks (Gunasekaran et al., 2015). This level of effort cannot be fully observed by the company, but it affects the probability of detecting defective products. The probability of outsourcing personnel detecting defective products depends on their level of effort and the type of ability they are capable of (Dong et al., 2016). The higher the level of effort and the type of ability, the higher the probability of detection. Outsourcing workers face increasing effort costs as the level of effort in quality checks increases. (Lee & Li, 2018). These costs can be time, energy, or lost opportunities to produce more products. Companies face losses when defective products pass to customers (Maharaj, 2019). These losses can be in the form of warranty fees, complaint handling, or reputational damage. Finally, both companies and outsourced personnel are assumed to act rationally to maximize their utility or profits.
In developing the Mathematical Model, the following notations and variables are used:

$i \epsilon I$: Index for outsourced personnel

$j \epsilon J$: Index for product type

$q \epsilon Q$: Index for product quality level ($q=1$ defective, $q = 2$ good)

p_j : The selling price of product type *j*

c_j : Production cost per unit product type *j*

e_i : Outsourced personnel effort level *i* in quality inspection

θ_i : Types of outsourced personnel's capabilities *i* (personal parameters)

π_j : Probability of product type *j* defects before check

δ_j : Company losses due to type-defective products *j* that pass to the customer

α : Defect detection sensitivity parameters to check efforts

β : Defect detection sensitivity parameters to the capabilities of outsourced personnel

γ : Marginal cost of quality check efforts

w_0 : Basic wage of outsourcing personnel per unit of product produced

w_i : Total wages for outsourced workers *i*

b_i: Bonuses for outsourcing personnel *i* if performing quality checks correctly

x_{ijq} : Number of product types *j* with quality *q* that are inspected by outsourced personnel *i*

y_{ijq} : Number of product types *j* with quality *q* reported by outsourcing personnel *i*

z_{ijq} : Number of product types *j* with quality *q* that passes to customers from outsourcing personnel *i*.

The probability of defect detection function, namely the probability of outsourced personnel *i* detecting defects in product types *j* defined as:

$$P_{ij}(e_i, \theta_i) = \alpha e_i + \beta \theta_i \qquad (1)$$

where $0 \leq P_{ij}(e_i, \theta_i) \leq 1, e_i \geq 0$ (effort level), and $\theta_i \epsilon [\underline{\theta}, \overline{\theta}]$ (ability type).

The α and β parameters (in equation 1) determine the sensitivity of the detection probability to the level of effort and capability type, respectively. (Dunn et al., 2019). The higher the α value, the greater the effect of the effort level on the probability of detection. The higher the β value, the greater the influence of the ability type on the probability of detection.

Based on the above notation and variables, the LP model can be formulated as follows:

Objectives function (Maximization of Company Profits)

$$Max \ \sum_{i\epsilon I}\sum_{j\epsilon J}\sum_{q\epsilon Q}(p_j - c_j - w_i)x_{ijq} - \sum_{i\epsilon I}\sum_{j\epsilon J}\delta_j z_{ij1} - \sum_{i\epsilon I} b_i \quad (2)$$

This objective function (2) maximizes the company's profits, which consist of revenue from product sales minus production costs, wages for outsourced personnel, losses due to defective products that pass to customers, and bonuses for outsourcing personnel.

IC requirements to ensure the honesty of outsourced personnel, the incentive to report honestly should be greater than the incentive to report dishonestly (Nasiri et al., 2023).

$$w_0 \sum_{j\epsilon J}\sum_{q\epsilon Q} x_{ijq} + b_i - \gamma e_i \geq w_0 \sum_{j\epsilon J}\sum_{q\epsilon Q} x_{ijq} + b_i\, P_{ij}(0, \theta_i)/P_{ij}(e_i, \theta_i) \quad (3)$$

further simplified to:

$$b_i \left(1 - \frac{P_{ij}(0,\theta_i)}{P_{ij}(e_i,\theta_i)}\right) \geq \gamma e_i \quad (4)$$

This requirement (4) is to ensure that outsourced personnel have an incentive to conduct quality checks with a level of effort e_i and report the checking results honestly, rather than making no effort at all ($e_i = 0$) and reporting results randomly.

IR requirements to ensure the participation of outsourced personnel, i.e. the expected utility must be greater than or equal to the reservation utility (Basu et al., 2019):

$$w_0 \sum_{j\epsilon J}\sum_{q\epsilon Q} x_{ijq} + b_i - \gamma e_i \geq U_0 \quad (5)$$

where U_0 is an outsourcing personnel reservation utility. This requirement (5) ensures that outsourced personnel are willing to participate in the incentive mechanism designed by the company.

Product balance requirements (6), i.e. the number of products inspected must be equal to the number of products reported:

$$\sum_{q\epsilon Q} x_{ijq} = \sum_{q\epsilon Q} y_{ijq}, \forall i \ \epsilon\ I, \forall j \ \epsilon\ J \quad (6)$$

Defect detection requirements (7) i.e. the number of defective products detected depend on the probability of detection:

$$y_{ij1} = x_{ij1} P_{ij}(e_i, \theta_i), \forall i \ \epsilon\ I, \forall j \ \epsilon\ J \quad (7)$$

Product requirements pass to customers (8) i.e. defective products that pass to customers:

$$z_{ij1} = x_{ij1} - y_{ij1}, \forall i \ \epsilon\ I, \forall j \ \epsilon\ J \quad (8)$$

and, good or undefective product that passes to the customer (9):

$$z_{ij2} = x_{ij2}, \forall\, i \in I, \forall\, j \in J \qquad (9)$$

Non-negative constraints are $x_{ijq}, y_{ijq}, z_{ijq}, w_i, b_i, e_i \ \geq 0, \forall\, i \in I, \forall\, j \in J, \forall\, q \in Q$.

To analyze the models that have been developed, analytical and numerical approaches are used (Akinsola & Oluyo, 2019). The analytical approach involves deriving the characteristics of the optimal solution from the LP model, including the optimal incentive structure, the optimal effort level, and the optimal examination allocation. The numerical approach involves sensitivity analysis to evaluate how changes in model parameters affect the optimal solution.

In particular, an analysis was carried out on how changes in the following parameters affect the optimal solution, namely losses due to defective products (δ_j), marginal cost of effort (γ), sensitivity parameter (α and β), and distribution of outsourced personnel types (θ_i). In addition, an analysis of the practical implications of the model for the company, outsourced personnel, and customer satisfaction was carried out.

RESULT AND DISCUSSION

Based on the LP developed, an analysis of the characteristics of the optimal solution for the outsourcing personnel incentive mechanism in product quality inspection was carried out. This analysis provides insights into optimal incentive structures, optimal effort levels, and optimal check allocation.

The optimal incentive structure consists of two components, namely the basic wage w_0 per unit of product produced and bonuses b_i^* which is given when the outsourcing personnel conduct quality checks correctly. From the requirements of the IC, it is obtained:

$$b_i^* = \gamma e_i^* \left(1 - \frac{P_{ij}(0,\theta_i)}{P_{ij}(e_i^*,\theta_i)}\right) \qquad (10)$$

This equation (10) shows that the optimal bonus b_i^* must be proportionate to the marginal cost of the audit effort γe_i^* and inversely proportional to the increased probability of defect detection resulting from such efforts (Peng et al., 2017). In other words, the higher the cost of the inspection effort, the greater the bonus required to encourage outsourcing personnel to conduct the inspection properly. Conversely, the greater the increased probability of defect detection resulting from the effort, the smaller the bonus required.
In addition, from the IR requirements, it is obtained:

$$w_0 \sum_{j \epsilon J} \sum_{q \epsilon Q} x_{ijq} + b_i^* - \gamma e_i^* \geq U_0 \qquad (11)$$

This equation (11) shows the combination of base wages and bonuses, minus the cost of the check effort, is at least equal to the utility of outsourcing personnel reservations. If these requirements are not met, the outsourcing personnel will not be willing to participate in the incentive mechanism designed by the company.

The optimal level of effort e_i^* for outsourced personnel type θ_i determined by the conditions:

$$\frac{\partial P_{ij}(e_i,\theta_i)}{\partial e_i} \sum_{j \epsilon J} \delta_j x_{ij1} = \gamma \qquad (12)$$

This equation (12) shows the optimal level of effort, the marginal benefit of increased defect detection (reduction of losses due to defective products) is equal to the marginal cost of the checking effort (Nas, 2016). With detection probability function $P_{ij}(e_i, \theta_i) = \alpha e_i + \beta\theta_i$, Obtained $\frac{\partial P_{ij}(e_i,\theta_i)}{\partial e_i} = \alpha$, so that:

$$\alpha \sum_{j\epsilon J} \delta_j x_{ij1} = \gamma \qquad (13)$$

From this equation (13), it can be seen that the optimal effort rate increases as the sensitivity of detection to effort increases. α, increased losses due to defective products δ_j, and an increase in the number of defective products inspected x_{ij1}. In contrast, the optimal effort rate decreases as the marginal cost of effort increases γ.

Optimal allocation of products for inspection x^*_{ijq} depends on a variety of factors, including the ability of outsourced personnel θ_i, probability of defective product π_j, and losses due to defective products δ_j. From the model analysis, it was found that outsourcing personnel with higher capabilities should be allocated to inspect products with a higher probability of defects and losses due to greater defects. For outsourced personnel with the same capabilities, the optimal allocation depends on the trade-off between the cost of inspection and the expected losses due to defective products passing to the customer.

Mathematically, the optimal allocation must meet the following conditions:

$$\frac{\partial}{\partial x_{ijq}}\left[(p_j - c_j - w_i)x_{ijq} - \delta_j z_{ij1}\right] = 0 \qquad (14)$$

This condition (14) shows that at the optimal allocation, the marginal benefit of allocating one additional unit of product for inspection is equal to the marginal cost. To understand how changes in LP model parameters affect the optimal solution, a sensitivity analysis of several key parameters was then carried out (Więckowski & Sałabun, 2024).

Effects of losses due to defective products δ_j, when losses due to defective products $\boldsymbol{\delta_j}$ increase (Figure 2), observable the following changes in the optimal solution. The optimal effort rate increases as the increase δ_j. This makes sense because the greater the losses due to defective products, the more important it is to increase the probability of defect detection through increased effort. Optimal bonuses increase as the increase of δ_j. This is due to an increase in the optimal effort rate, which requires a greater bonus to meet the IC requirements. Inspection allocation, products with greater defect losses get higher priority in inspection allocation, especially for outsourced personnel with higher capabilities (Lee & Li, 2018).

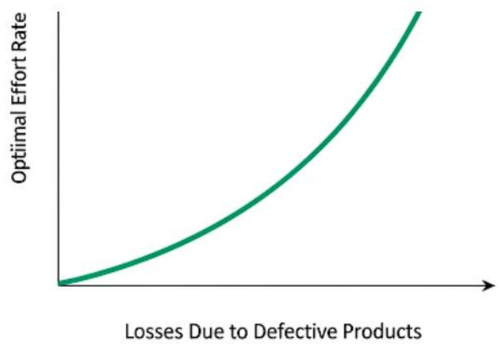

Figure 2. Relationship Between Losses Due to Defective Product and Optimal Effort
Source: Lee & Li, 2018

Overall, increased losses due to defective products cause companies to provide greater incentives for quality checks and allocate more resources to products with higher failure consequences. The effect of marginal costs of effort γ, when the marginal cost of effort γ increases, can be observed in the following changes in the optimal solution. The optimal effort rate decreases as the increase γ (Figure 3). This is due to the intuition that the higher the cost of effort, the lower the optimal level of effort from the perspective of economic efficiency (Dong et al., 2016). The optimal bonus increases per unit of effort, but may decrease overall due to a decrease in the optimal effort rate.

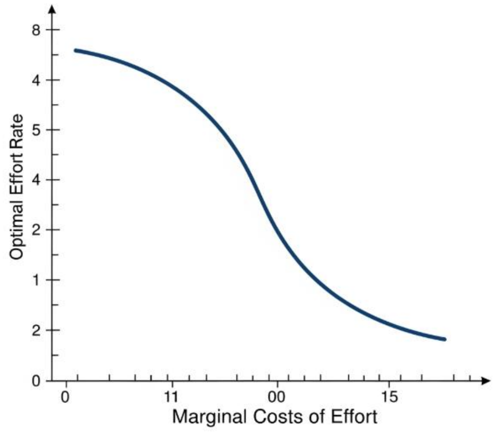

Figure 3. Relationship Between Marginal Costs of Effort and Optimal Effort Rate
Source: Dong et al., 2016

Mathematically:

$$\frac{\partial b_i^*}{\partial \gamma} = \frac{e_i^* + \gamma \frac{\partial e_i^*}{\partial \gamma}}{1 - P_{ij}(0,\theta_i)/P_{ij}(e_i^*,\theta_i)} - \frac{\gamma e_i^* \frac{\partial}{\partial \gamma}(P_{ij}(0,\theta_i)/P_{ij}(e_i^*,\theta_i))}{\left(1 - P_{ij}(0,\theta_i)/P_{ij}(e_i^*,\theta_i)\right)^2} \qquad (15)$$

The sign of this derivative (15) depends on the amount of the decrease in the optimal effort rate relative to the increase in marginal costs. The company's profits decline along with the increase γ, because the company has to pay a larger bonus per unit of effort or receive a lower effort rate, both of which reduce profits. These results show the trade-off between the effort of the examination and the cost of incentives (Monghasemi et al., 2015). If quality checks become more laborious or require more time (higher marginal effort costs), companies need to provide greater incentives per unit of effort but may expect lower effort rates overall.

The influence of sensitivity parameters α and β, parameters α and β determine the sensitivity of the probability of defect detection to the level of effort and type of ability, respectively. The sensitivity analysis to these parameters provides the following insights (Table 1).

When α (sensitivity to effort) increases, optimal effort level e_i^* increases as efforts become more effective in increasing the probability of detection. Bonus optimal b_i^* may decrease due to higher effort effectiveness, even if the effort rate increases. The company's profits increased due to increased effectiveness of efforts in detecting defective products (Porter & Heppelmann, 2015).

When β (sensitivity to capabilities) increases, the difference in the allocation of checks between outsourced personnel with different capabilities becomes more significant.

Companies must be more selective in choosing outsourced personnel for quality inspection tasks, by giving higher priority to outsourced personnel with higher capabilities. The company's profits increase due to the increased effectiveness of the ability to detect defective products (Realyvásquez-Vargas et al., 2018).

Table 1. Sensitivity Analysis

Parameter Change	Impact on Variables	Insight
When sensitivity to effort increases	• Optimal effort level increases. • Optimal bonus may decrease. • Company profit increases.	• Effort becomes more effective at increasing the probability of defect detection. • The higher effectiveness of effort may reduce the bonus needed to meet Incentive Compatibility requirements, even as the effort level rises. • Increased effectiveness in detecting defective products leads to higher profits.
When sensitivity to capabilities increases	• Inspection allocation becomes more significant between personnel with different capabilities. • Companies must be more selective. • Company profit increases.	• A higher sensitivity makes the difference in personnel capabilities more pronounced in defect detection. • Companies should prioritize personnel with higher capabilities for inspection tasks. • The increased effectiveness of capabilities in defect detection leads to higher profits.

Source: Authors' work, 2025

Distribution of outsourced workforce types θ_i has important implications in the design of incentive mechanisms. The results of the analysis show that the variation in capabilities, i.e. when the variation in the capabilities of outsourced personnel increases, the design of incentive mechanisms becomes more complex. Companies need to implement different contract menus for different types of outsourced personnel, which can increase administrative costs (Akkermans et al., 2019). However, companies can also take advantage of this variation by allocating outsourced personnel with higher capabilities to products with higher failure consequences. As the average ability increases, the optimal effort level may decrease because the ability and effort are substitutions in the detection probability function (Kim et al., 2018). The optimal bonus may decrease due to the higher probability of basic (effortless) detection. The company's profits increase due to the increased probability of defect detection.

Based on the analysis of the model above, there are several practical implications for companies in designing incentive mechanisms. The company must design an optimal contract with outsourced personnel that includes a fixed wage component based on the amount of production and a bonus component based on quality inspection performance (Abdullah et al., 2021). The bonus structure should be adjusted to the cost of the examination effort and the effectiveness of the effort in increasing the probability of defect detection. Companies need to develop verification mechanisms to assess the accuracy of the examination, which may involve sample examination or periodic audits.

Companies must assess the capabilities of outsourcing personnel before assignment, either through tests or probationary periods (Sampson & dos Santos, 2023). Outsourced personnel with higher capabilities should be allocated to inspect products with a higher probability of defects or losses due to greater defects. Companies need to consider investing in training to improve the capabilities of outsourced personnel, especially if the sensitivity parameter to capability (β) is high.

Companies need to develop a monitoring system to assess the accuracy of quality checks, involving sample checks or periodic audits. Timely feedback to outsourcing personnel on their audit performance can help improve accuracy and build trust in the incentive system (Asif, 2022). The Company periodically evaluates and adjusts the parameters of the incentive mechanism based on performance data and changes in the business environment.

Companies need to conduct a cost-benefit analysis to compare the costs of incentive mechanisms with the reduction of losses due to defective products (Coplan, 2017). The trade-off between quality check costs and customer satisfaction needs to be evaluated explicitly. The allocation of resources for quality inspection is optimized based on cost-benefit analysis.

The incentive mechanism designed based on this model also has important implications for outsourced personnel. Outsourcing personnel can increase revenue through quality inspection bonuses, which compensate for additional effort in inspections. A well-designed incentive structure ensures outsourced personnel are fairly rewarded for their extra efforts. Outsourcing personnel have a clear path to increasing revenue through improved skills and inspection capabilities. Outsourced personnel are encouraged to improve quality inspection capabilities, to increase their value to the company. They can learn more efficient inspection techniques to reduce effort costs while maintaining accuracy. The development of expertise in detecting product defects can open up new career opportunities in quality control. Balancing quantity and quality, outsourcing personnel need to balance quantitative production goals (the number of products produced) and qualitative goals (accuracy of quality checks). They need to allocate time and effort optimally between production and inspection to maximize their revenue. A well-designed incentive structure helps align the goals of outsourcing with the company's goals (Kang et al., 2022).

The implementation of effective incentive mechanisms for quality checks has positive implications for customer satisfaction (Zhao et al., 2019). Improved product quality by reducing the number of defective products reaching customers improves customer experience. Improving product quality consistency builds customer trust in the brand. Reduced warranty costs and complaint handling allow companies to offer more competitive prices or improve product features. With increased customer trust, with better product quality, the company can build a reputation for quality and reliability. Increased customer trust can increase customer loyalty and repeat purchases. Companies can gain a competitive advantage in the market through quality differentiation. Customer feedback on product quality can be used to adjust the parameters of the incentive mechanism. Companies can identify areas for improvement in the inspection process based on customer complaint patterns.

Although the model developed in this study provides valuable insights into the design of incentive mechanisms for outsourcing personnel in product quality inspection, this model has some limitations. The model assumes the company can verify the results of quality checks, which may not always be practical in a real-world setting. The model also assumes that the distribution of outsourced workforce capability types is known, which may be difficult to estimate accurately. The relationship between effort and detection probability is assumed to be linear, which may be a simplification of a more complex relationship. The complexity of practical implementation, the model faces challenges in estimating accurate model parameters, which require historical or experimental data. The design of an effective monitoring system to assess the accuracy of quality checks can be complex and expensive. Communicating the incentive structure to outsourced workers clearly and transparently can be challenging. Dynamic factors, the model does not fully capture the learning and upskilling of outsourced personnel over time. Social dynamics and teamwork among outsourced workers are not considered in the model. Changes in production technology and inspection methods may affect the parameters of the model over time (Chen et al., 2021).

Based on these limitations, several directions for future research. Expand the model to account for learning and temporal dynamics, including how capabilities and costs of effort change over time. Integrate social and psychological factors in incentive design, such as intrinsic motivation, social norms, and peer effects. Develop models for scenarios with more limited information, where the company cannot fully verify the results of quality checks. Next, conduct empirical studies to validate model predictions in real-world settings, including field experiments or case studies. Estimate key model parameters from industry data, including effort cost, detection sensitivity, and capability distribution. Evaluate the effectiveness of different incentive mechanisms in improving product quality and customer satisfaction.

CONCLUSION

This research develops an incentive mechanism model based on Mechanism Design Theory and Linear Programming to encourage outsourcing personnel to conduct honest and optimal product quality inspections. This model is designed by considering two main principles, namely Incentive Compatibility to ensure honesty of reporting, and Individual Rationality to ensure the participation of outsourced personnel. The results of the analysis show that incentives consisting of a combination of basic wages and bonuses based on inspection quality can align the interests of the company and outsourced personnel. The level of optimal product quality inspection efforts increases in line with the increase in losses due to defective products and the effectiveness of efforts, while the allocation of inspections should be given to outsourced personnel with higher capabilities on products at high risk of defects.

This model has some limitations. Assumptions about the company's ability to verify the results of the audit and know the distribution of the capabilities of outsourced personnel may not be realistic in the field. The relationship between effort and detection probability assumed to be linear also simplifies complexity in the real world. In addition, aspects of learning, social dynamics, and examination technology have not been included in the model.

For future development, it is recommended that the study expand the model by taking into account temporal dynamics such as learning and cost changes, as well as integrating social-psychological factors and verification limitations. In the future, it is necessary to conduct empirical research through direct interviews with samples or sources from two parties, namely a minimum of three sourcing personnel and a quality control manager, to validate the effectiveness of the model in real industrial practice.

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