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# IDENTIFICATION OF RISK FACTORS AFFECTING SUGAR DISTRIBUTION EFFICIENCY AT PT. XYZ USING EXPLORATORY FACTOR ANALYSIS (EFA)

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**ABSTRACT**

Distribution efficiency is a critical element in sugar supply chain management, but PT XYZ experienced a 62% increase in distribution risk cases from 2023 to 2025, with financial losses reaching IDR 92 million. This study aims to identify and categorize risk factors that affect sugar distribution efficiency using the Exploratory Factor Analysis (EFA) method. A quantitative approach was used with data collection through questionnaires distributed to 60 respondents directly involved in distribution operations at PT XYZ, Lampung Province. The analysis used EFA with Principal Axis Factoring extraction and Varimax rotation, supported by JASP software. Although the KMO value was marginal (0.491), the data proved to be suitable for analysis, supported by a significant Bartlett's Test ($\chi^2$ = 507.988, $p < 0.001$) and a good model fit ($\chi^2$ = 197.411, $p$ = 0.253). Five main factors were successfully extracted, explaining 40.5% of the total variance, namely Technical and Environmental Risk with Information Response (10.5% variance), Distribution Efficiency (8.2% variance), Operational Risk (7.7% variance), Human Resource Technical Competence and Compliance (7.2% variance), and Human Resource Interpersonal Competence (6.9% variance). The most significant findings show that teamwork skills (SDM5) have the highest factor loading (0.972), followed by administrative readiness (RO4, 0.843), and SOP compliance (SDM1, 0.834). Distribution efficiency at PT XYZ is largely determined by human factors, particularly the ability of employees to collaborate effectively in cross-functional teams, followed by an organized operational system and procedural discipline. The information system functions as an enabler rather than an independent risk factor. These findings provide practical insights for management to prioritize team development programs, operational system optimization, and procedural compliance strengthening to improve distribution efficiency.

***Keywords :*** *Distribution Efficiency, Exploratory Factor Analysis, Risk Management, Sugar Distribution, Human Resource Competency*

## 1. INTRODUCTION

Distribution is a vital element in the logistics system that serves as a link between producers and end consumers. In the context of modern supply chain management, distribution not only involves the physical movement of goods but also involves information coordination, route optimization, fleet management, and integration between various stakeholders (Chopra & Meindl, 2020). Distribution efficiency is a key indicator of logistics operational success because it directly affects three crucial aspects, namely operational costs, service speed, and customer satisfaction. Research by Christopher (2016) shows that distribution costs can reach 30-40% of total logistics costs , so improving distribution efficiency has the potential to have a significant impact on company profitability.

In the Fast-Moving Consumer Goods (FMCG) industry, including strategic commodities such as sugar, efficient distribution plays a very important role. Sugar is one of the basic necessities of the Indonesian people, with national consumption reaching 6.8 million tons per year (Ministry of Trade, 2024). The characteristics of sugar as a bulk commodity, requiring large volumes for shipment and being sensitive to humidity, make its distribution system face complex challenges. Inefficient sugar distribution not only increases companies' operating costs, but can also cause delays in market supply, price fluctuations that harm consumers, and a decline in product quality due to prolonged storage (Bakdiyah et al., 2020).

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The sugar distribution sector in Indonesia faces various structural challenges that hinder the achievement of optimal efficiency. The uneven quality of road infrastructure, especially in areas outside Java, causes inconsistent travel times and increases the risk of damage to goods during transit (Dharmawan et al., 2021). High fuel price fluctuations have a direct impact on transportation costs, which are difficult to predict. Limited availability of adequate transportation fleets, particularly vehicles specifically designed for bulk commodities, forces distributors to operate at suboptimal capacity. In addition, inaccurate information and weak coordination among parties involved in the distribution chain often result in delivery errors, delays, and waste of resources (Fauzi & Rahayu, 2022). These challenges are even more complex given the unstable dynamics of the national sugar supply, where in 2025 the government plans to import around 200,000 tons of raw sugar to maintain national stock availability, indicating that attention to distribution efficiency is becoming increasingly urgent.

PT XYZ is one of the companies engaged in sugar distribution in Lampung Province with regional to national service coverage. In recent years, the company has recorded an increase in shipping volume in line with growing market demand. However, this increase in distribution activity has not always been accompanied by improved efficiency. This condition indicates that operational growth has the potential to create new risks which, if not managed properly, could reduce overall distribution efficiency. The following is PT. XYZ's transportation risk data for the 2023-2025 period :

**Table 1**. 1 Transportation Distribution Risk Data for PT XYZ for the 2023–2025 Period

| Year | Number of Shipments (times) | Delays (cases) | Damaged Goods (cases) | Wrong Destination (cases) | Total Risk Cases | Risk Percentage | Losses (IDR) |
|---|---|---|---|---|---|---|---|
| 2023 | 1,221 | 45 | 30 | 20 | 95 | 7.9% | 55,000,000 |
| 2024 | 1,450 | 63 | 38 | 24 | 125 | 8.6% | 73,000,000 |
| 2025 | 1,678 | 79 | 46 | 29 | 154 | 9.1% | 92,000,000 |

Source : Transportation Distribution Risk Data PT. XYZ 2023–2025, processed by the author (2025)

Based on the data in the table above, PT. XYZ during the 2023–2025 period, sugar distribution activities showed an increase in the number of shipments followed by an increase in distribution risk cases. The identified risks include delivery delays, damage to goods, and delivery destination errors. Although the percentage of risk cases is relatively small compared to the total number of shipments, the consistent upward trend indicates that distribution risk is an issue that needs serious attention in efforts to improve distribution efficiency.

In 2023, there were 95 risk cases with financial losses of IDR 55,000,000. This number increased to 125 cases with losses of IDR 73,000,000 in 2024, and increased again to 154 cases with losses of IDR 92,000,000 in 2025. This increase indicates that distribution risks not only impact operational aspects but also have significant financial consequences for the company. Thus, distribution risks are an important factor that could potentially affect the level of sugar distribution efficiency at PT XYZ.

Several previous studies have identified various factors that affect the smoothness and efficiency of distribution in the sugar and similar commodity industries. Bakdiyah et al. (2020) in their study at the Mojo Sugar Factory identified 12 types of risks in the sugar supply chain with high to very high risk levels, including operational risks, financial risks, and external risks. The study emphasizes the importance of systematic risk identification to maintain supply chain sustainability. Nurhayati and Putra (2021), in their study on distribution risk management in the food industry, found that the three main factors causing inefficiency were delivery delays, errors in the distribution process, and a lack of coordination of information between departments. Santoso (2022), through an empirical analysis of food commodity distribution companies in Indonesia, revealed that the three key elements of successful distribution in the agribusiness sector are human resource competence, transportation fleet conditions, and the effectiveness of the distribution information system. Meanwhile, Harsanto et al. (2022), in their study on the performance of the national sugar industry supply chain, found that information technology, operational capabilities, and organizational culture significantly affect distribution performance.

Although these studies have made important contributions to understanding distribution risks, there are several research gaps that need to be bridged. First, most of the previous studies are descriptive in nature and use a qualitative approach or single case studies, so they do not provide strong empirical validation of the latent structure of risk factors. Second, previous studies tend to focus on production or upstream supply chain management aspects, with limited attention to the final distribution phase at the regional level. Third, there has been no study that specifically uses Exploratory Factor Analysis (EFA) to identify and group sugar distribution risk factors in Indonesia based on empirical field data. Fourth, previous studies have not comprehensively explored the interactions between various risk dimensions (operational, technical, human resources, and information) in the context of distribution efficiency.

Based on the identification of problems and research gaps above, the problems faced by PT XYZ can be formulated as follows. First, even though the company has implemented an Enterprise Resource Planning (ERP) system and an internal risk management program, distribution risk cases have actually increased by 62% in the 2023-2025 period, with financial losses reaching IDR 92 million. Second, the specific risk factors that most significantly affect the decline in distribution efficiency have not been identified, so management interventions have not been on target. Third, there is no clear understanding of the structure and relationships between the various risk dimensions that can be used as a basis for developing a comprehensive risk mitigation strategy. Fourth, an analysis method is needed that can reveal the latent patterns of the complexity of risk factors that interact within the sugar distribution system. Therefore, this research is important to identify the empirical structure of risk factors and provide data-based recommendations that can improve distribution efficiency at PT XYZ.

This study aims to identify and group risk factors that affect the efficiency of sugar distribution at PT XYZ using the Exploratory Factor Analysis (EFA) method. The EFA method was chosen based on its ability to reveal the latent structure of intercorrelated variables and group them into main factors without any initial assumptions about the structure (Hair et al., 2019). This approach allows for the objective identification of risk dimensions that may not be explicitly visible in direct observation.

The novelty of this research lies in several aspects. First, this study applies a multivariate statistical method (EFA) to identify the factor structure of sugar distribution risks. Previous studies have mostly used qualitative descriptive methods and case study analysis. Second, there have been few studies on this subject in the context of the sugar industry in Indonesia, as special treatment is required to handle sugar products, which are bulk commodities and sensitive to moisture. Previous studies have mostly discussed the distribution of manufactured products, retail, and other agricultural commodities such as rice or vegetables. Third, this study integrates various risk dimensions (operational, technical-environmental, human resources, and information accuracy) into a comprehensive analytical framework to understand their influence on distribution efficiency. Fourth, this study not only identifies risk factors descriptively but also measures the relative importance of each factor through factor loading, thereby providing clear priorities for managerial intervention. Fifth, this study was conducted in the context of a company that has implemented an ERP system and risk management but still experiences a decline in efficiency, thus providing insight into why technology investments do not always result in the expected performance improvements.

This study is expected to contribute both theoretically and practically. From a theoretical perspective, this study enriches the supply chain risk management literature by identifying the latent structure of distribution risk factors using a quantitative empirical approach, as well as providing empirical validation of risk constructs that have been discussed more conceptually. From a practical perspective, the findings of this study can help the management of PT XYZ and other sugar distribution companies understand which risk factors most influence distribution efficiency, prioritize resource allocation for the most critical risk mitigation, design targeted competency development programs and operational systems, and formulate data-driven strategies for improving distribution efficiency. Thus, this study not only fills a gap in the academic literature but also produces actionable recommendations for improving sugar distribution efficiency at the regional and national levels.

## 2. METHOD

The research method used is a quantitative approach with the aim of recognizing and categorizing risk factors that affect the effectiveness of sugar distribution at PT XYZ. This approach was chosen based on the exploratory nature of the research, which focuses on identifying the main factors that cause inefficiency in distribution. The research was conducted at PT XYZ, a company that focuses on sugar distribution in the Lampung area. The research subjects included all distribution activities related to fleet operations, labor, information systems, and external factors that could potentially cause risks in the distribution process.

The data used in this study was collected through questionnaires distributed to PT XYZ employees directly involved in the distribution process, such as drivers, logistics personnel, and fleet coordinators. Respondents were selected using purposive sampling with a minimum requirement of six months of employment. The population in this study was all PT XYZ employees directly involved in sugar distribution operations in the Lampung Province. Based on data from the PT XYZ Human Resource Department as of December 2024, the total population was 127 people consisting of four job categories, namely drivers and staff (with more than 10 years of experience), supervisors and managers in each distribution and transportation department, as well as warehouses. The sample size for this study was 60 people, determined using the Slovin formula with a margin of error of 10%:

$$n = \frac{N}{1 + N \cdot e^2}$$

- N = Population Size (127)
- e = Margin of Error (10% or 0.01)
- n = Sufficient Sample Size is 55.95 (rounded to 56)

$$n = \frac{127}{1 + 127 \times 0.10^2} = \frac{127}{1 + 127 \times 0.01} = \frac{127}{1 + 1.27} = \frac{127}{2.27} = 55.95 \approx 56$$

The questionnaire itself uses a Likert scale from 1 to 5 to assess the level of influence of each risk factor on distribution efficiency. In addition to the primary data obtained from the questionnaire, this study also combines secondary data in the form of shipping data and company distribution risk data for the 2023–2025 period. The following is a table of the operational definitions of the variables in this study:

**Table 2**.1 Operational Definitions of Variables

| Variable | Definition | Number of Items | Item Code | Reference |
|---|---|---|---|---|
| **Operational Risk (OR)** | Risks from daily operational activities that can disrupt the smooth flow of distribution | 5 | OR1 - OR5 | Tang (2006) |
| **Technical & Environmental Risk (RT)** | Risks from technical factors related to equipment and external environmental conditions | 5 | TR1 - TR5 | Waters (2011) |
| **Human Resource Risk** | Risks related to human resource competence, compliance, and behavior | 5 | HR1 - HR5 | Santoso (2022) |
| **Information Accuracy (IA)** | The quality and speed of information systems in supporting distribution coordination | 5 | KI1 - KI5 | Chopra & Meindl (2020) |

Source : Processed by the author (2025)

Data analysis was performed using Exploratory Factor Analysis (EFA). This approach was used to identify and group interrelated risk variables into several key factors. The steps in the analysis included examining data suitability using KMO and Bartlett's Test, factor extraction using principal component analysis, factor rotation to clarify the relationship between variables, and factor interpretation based on factor loading values. The results of the analysis were then described to find the most significant risk factors affecting sugar distribution efficiency at PT XYZ. This study is expected to provide better insight into the main sources of risk and serve as a foundation for the company in developing more efficient mitigation strategies.

## 3. RESULT AND DISCUSSION

### Result

The Exploratory Factor Analysis (EFA) method was used to examine and identify the main risk factors affecting sugar distribution efficiency at PT. XYZ. This analysis used JASP software as a tool for thinking and making discussions in stages. JASP was used because of its user-friendly design, support for various statistical tests, and its ability to automatically display KMO values, Bartlett's test, communalities, and factor rotation.

In this study, for data processing, a questionnaire was distributed to identify risk factors that affect distribution efficiency at PT. XYZ. Information was collected using a 1-5 Likert scale, where :

**Table 3**.1 Likert Scale 1-5 Table

| Scale | Description |
|---|---|
| 1 | Strongly Disagree |
| 2 | Disagree |
| 3 | Neutral |
| 4 | Agree |
| 5 | Strongly agree |

Source : Compiled by the author (2025)

A total of 60 respondents were involved, coming from various departments that function directly in distribution and transportation, as well as warehousing. The sampling technique used was purposive sampling, consisting of drivers and staff (with more than 10 years of experience), supervisors and managers in each distribution and transportation department, as well as warehousing.

**3.1 Data Feasibility Test**

Before conducting factor analysis, data validity testing was performed to ensure the data met the requirements for Exploratory Factor Analysis (EFA).

**3.1.1 Slovin Test**

$$n = \frac{N}{1 + N \cdot e^2}$$

- N = Population Size (127)
- e = Error Rate (10% or 0.01)
- n = Sufficient Sample Size is 55.95 (rounded to 56)

Based on calculations using the Slovin formula, with a population size of 127 and an error rate of 10%, the minimum sample size required is 56. In the context of this study, the use of 60 respondents met the statistical requirements and was considered representative of the population. This provides confidence that the data obtained is valid enough to analyze risk factors.

**3.1.2 Kaiser-Meyer-Olkin (KMO) and Bartlett's Test**

The KMO test results show an Overall MSA value of 0.491. According to Kaiser (1974), the KMO value can be interpreted as follows: 0.90+ (excellent), 0.80-0.89 (meritorious), 0.70-0.79 (middling), 0.60-0.69 (mediocre), 0.50-0.59 (poor), and <0.50 (unacceptable). With a value of 0.491, this data is at the minimum threshold for EFA analysis.

Although the Overall MSA value is below 0.50, several individual items show fairly good to good MSA values, such as :

- KI5 (0.739) - Good
- RT5 (0.701) - Good
- RT2 (0.692) - Mediocre-Good
- ED3 (0.624) - Mediocre
- ED1 (0.583) - Poor-Mediocre
- SDM1 (0.564) - Poor-Mediocre

These varying individual MSA values indicate that although the overall sampling adequacy is marginal, some variables have sufficient correlation patterns for factor analysis. This suggests that the analysis can be continued with careful interpretation.

The Bartlett test produced a Chi-Square value of 507.988 (df = 300, $p < 0.001$), which is statistically significant. This result indicates that the correlation matrix between variables is not an identity matrix, so there is a significant correlation to perform factor analysis.

**3.1.3 Chi-Squared Test Model Fit**

The Chi-Square test for model fit produced a value of 197.411 (df = 185, p = 0.253). The insignificant p-value ($p > 0.05$) indicates that the model fits the data well, meaning that the extracted factor structure is statistically consistent with the observed data. Conclusion of Feasibility: Based on Bartlett's highly significant test and good Model Fit, the data is feasible for EFA analysis even though the KMO value is at the minimum limit.

**Table 3**.2 Chi-Squared Test

| *Chi-Squared Test* | | | |
|---|---|---|---|
| | Value | df | p |
| Model | 197.411 | 185 | .253 |

Source : Processed by the author (2025)

### 3.2 Factor Extraction and Characteristics

Based on the results of EFA analysis using the Principal Axis Factoring extraction method and Varimax rotation (orthogonal rotation), five factors were extracted from the 25 questionnaire items. These five factors were able to explain 40.5% of the cumulative variance of the overall data. The following table shows the characteristics of each factor before and after rotation :

*Factor Characteristics*

| | Unrotated solution | | | Rotated solution | | |
|---|---|---|---|---|---|---|
| | Eigenvalue | Proportion var. | Cumulative | SumSq. Loadings | Proportion var. | Cumulative |
| Factor 1 | 3.173 | 0.127 | 0.127 | 2.614 | 0.105 | 0.105 |
| Factor 2 | 2.160 | 0.086 | 0.213 | 2.040 | 0.082 | 0.186 |
| Factor 3 | 1.859 | 0.074 | 0.288 | 1.917 | 0.077 | 0.263 |
| Factor 4 | 1.623 | 0.065 | 0.353 | 1.807 | 0.072 | 0.335 |
| Factor 5 | 1.394 | 0.056 | 0.408 | 1.736 | 0.069 | 0.405 |

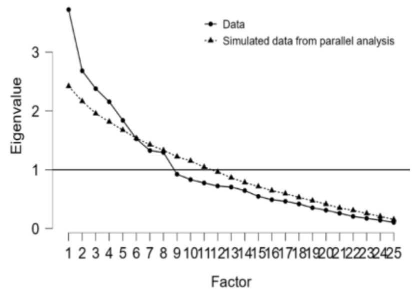


**Figure 3**.1 Factor Characteristics and Scree Plot

Source : Author's elaboration (2025)

Based on Kaiser's criterion (eigenvalue > 1.0), all five factors are worth retaining. The scree plot shows a sharp decline after Factor 1, then a gradual decline from Factor 2 to Factor 5, indicating that Factor 1 contributes the largest variance (10.5%), while the other four factors contribute relatively evenly.

### 3.3 Interpretation of Factor Loadings

Factor loadings indicate the strength of the relationship between each item and the extracted factor. The criterion used is that factor loadings ≥ 0.40 are considered significant (Hair et al., 2019). The following is a detailed interpretation for each factor :

*Factor Loadings*

| | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 | Uniqueness |
|---|---|---|---|---|---|---|
| RT5 | 0.732 | | | | | 0.408 |
| RT4 | 0.728 | | | | | 0.451 |
| RT3 | 0.634 | | | | | 0.578 |
| RT2 | 0.495 | | | | | 0.739 |
| KI5 | -0.484 | | | | | 0.706 |
| KI2 | -0.445 | | | | | 0.695 |
| ED4 | | 0.861 | | | | 0.193 |
| ED1 | | 0.553 | | | | 0.649 |
| ED5 | | 0.501 | | | | 0.672 |
| ED2 | | 0.448 | | | | 0.673 |
| RO4 | | | 0.843 | | | 0.264 |
| RO5 | | | 0.634 | | | 0.513 |
| RO3 | | | 0.486 | | | 0.687 |
| RO1 | | | 0.411 | | | 0.752 |
| SDM1 | | | | 0.834 | | 0.285 |
| SDM2 | | | | 0.564 | | 0.575 |
| SDM5 | | | | | 0.972 | 0.005 |
| SDM4 | | | | | 0.583 | 0.632 |
| ED3 | | | | | | 0.689 |
| KI1 | | | | | | 0.875 |
| KI3 | | | | | | 0.794 |
| KI4 | | | | | | 0.928 |
| RO2 | | | | | | 0.729 |
| RT1 | | | | | | 0.633 |
| SDM3 | | | | | | 0.761 |

*Note.* Applied rotation method is varimax.

**Figure 3**.2 Factor Loadings
Source : Author's elaboration (2025)

**Factor 1 Technical and Environmental Risk (10.5% variance)**

**Table 3**.3 Factor 1 Technical and Environmental Risk

| Item | Loading | Interpretation |
|---|---|---|
| RT5 | 0.73 | Goods rarely suffer damage during transport |
| RT4 | 0.728 | Weather does not significantly disrupt the distribution process |
| RT3 | 0.634 | Road/terrain conditions rarely hinder delivery |
| RT2 | 0.495 | Distribution support facilities are adequate |
| KI5 | -0.484 | Communication between distribution departments is good |
| KI2 | -0.445 | Distribution information is communicated quickly |

Source : Author's compilation (2025)

This factor is dominated by the Technical and Environmental Risk variables with positive loadings (0.495-0.732). Interestingly, there are negative loadings on KI2 and KI5, indicating a compensation mechanism, whereby when technical risks increase (adverse conditions), the need for rapid communication and coordination becomes even more crucial. The information system acts as a buffer against unfavorable external conditions.

**Factor 2 Distribution Efficiency (8.2% variance)**

**Table 3**.4 Factor 2 Distribution Efficiency

| Item | Loading | Interpretation |
|---|---|---|
| ED4 | 0.861 | The distribution process runs quickly and smoothly |
| ED1 | 0.553 | Goods arrive on time at their destination |
| ED5 | 0.501 | Customers are satisfied with the distribution service |
| ED2 | 0.448 | Distribution is carried out at a controlled cost |

Source : Author's compilation (2025)

This factor certainly reflects Distribution Efficiency as a concept that has many dimensions, including process speed (the most significant indicator, 0.861), timeliness, customer satisfaction, and cost control. The highest weight in ED4 shows that process speed and smoothness are the indicators that best describe distribution efficiency.

**Factor 3 Operational Risk (7.7% variance)**

**Table 3**.5 Factor 3 Operational Risk

| Item | Loading | Interpretation |
|---|---|---|
| RO4 | 0.84 | Administration and shipping documents are ready |

| | | |
|---|---|---|
| RO5 | 0.634 | Errors in the distribution process are rare |
| RO3 | 0.486 | Goods are carefully inspected before shipment |
| RO1 | 0.411 | The shipping route is well planned |

Source : Author's compilation (2025)

This factor represents Operational Risk very well. The highest loading on RO4 (0.843) indicates that administrative and documentation readiness is the most crucial foundation in operational risk management. The loading order shows the hierarchy: administrative readiness > error minimization > goods inspection > route planning.

**Factor 4 Compliance and Technical Competence of Human Resources (7.2% variance)**

**Table 3**.6 Factor 4: Compliance and Technical Competence of Human Resources

| Item | Loading | Interpretation |
|---|---|---|
| HR1 | 0.83 | Always comply with SOPs in the distribution process |
| SDM2 | 0.564 | Able to operate distribution technology |

Source : Author's compilation (2025)

This factor combines procedural compliance (SDM1) and technical competence (SDM2). The very high loading on SDM1 (0.834) indicates that SOP compliance is a fundamental aspect of distribution human resource competence. This combination is logical because technical competence will be optimal when performed in accordance with SOPs.

**Factor 5 Interpersonal Competence of Human Resources (6.9% variance)**

**Table** 3.7 Factor 5: Interpersonal Competence of Human Resources

| Item | Loading | Interpretation |
|---|---|---|
| HR5 | **0.972** | Able to work well in a team |
| SDM4 | 0.583 | Responsible in completing tasks |

Source : Author's compilation (2025)

This factor has the highest loading in the entire analysis (SDM5 = 0.972) with very low uniqueness (0.005), meaning that 99.5% of the variance is explained by this factor. These results indicate that teamwork is the most important HR factor in distribution operations. This item almost perfectly represents the soft skills dimension of HR.

**Path Diagram**

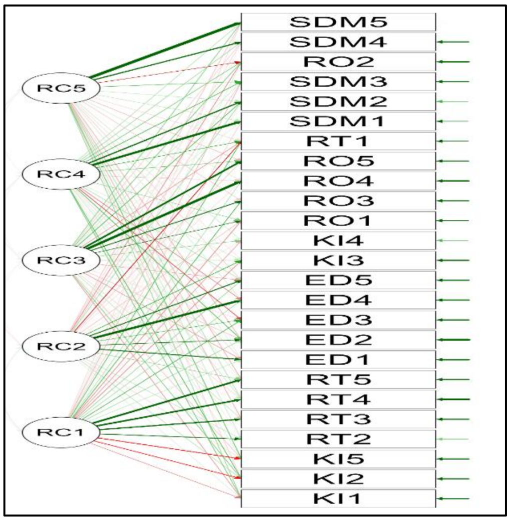


**Figure 3**.3 Path Diagram

Source : Author's compilation (2025)

The figure above shows the path diagram of the EFA analysis results, which visualizes the relationship between the five latent factors (RC1-RC5) and 25 observed items. In the path diagram of the EFA analysis results, the notations RC1 to RC5 are abbreviations for Rotated Component, which represent the five latent factors resulting from extraction and Varimax rotation. Specifically:

- RC1 (Rotated Component 1) = Factor 1 Technical and Environmental Risk with Information Response
- RC2 (Rotated Component 2) = Factor 2 Distribution Efficiency
- RC3 (Rotated Component 3) = Operational Risk Factor 3
- RC4 (Rotated Component 4) = Factor 4 Compliance and Technical Competence of Human Resources
- RC5 (Rotated Component 5) = Factor 5 Interpersonal Competence of Human Resources

The thickness of the lines indicates the strength of the factor loading, where thick green lines indicate high loading (> 0.60), thin lines indicate moderate loading (0.40 -0.60), and red lines indicate negative loading.

This diagram clearly shows that SDM5 (teamwork) has the highest loading, as indicated by the thickest line leading to RC5, with a value of 0.972. Other factors with strong loadings are RO4 (administrative readiness) with a loading of 0.843 to RC3, ED4 (process speed) with a loading of 0.861 to RC2, and SDM1 (SOP compliance) with a loading of 0.834 to RC4.Interestingly, there are red lines from RC1 to KI2 and KI5, indicating a negative relationship between technical-environmental risk factors and information accuracy items, which shows a compensation mechanism where information needs increase when external conditions deteriorate.

**Items with High Uniqueness**

Several items have high uniqueness values (>0.70), meaning that most of their variance is not explained by the five extracted factors:

**Table 3**.8 Items with High Uniqueness

| Item | Uniqueness | Interpretation |
|---|---|---|
| KI4 | 0.928 | Easy access to information through the system/mobile phone |
| KI1 | 0.875 | Information on the status of goods is always accurate |
| KI3 | 0.794 | Data and documents are easy to understand |
| SDM3 | 0.761 | Always prioritizes work safety |
| RO2 | 0.729 | Loading and unloading processes are completed on time |

Source : Author's compilation (2025)

These items have unique characteristics that are not well grouped within the existing factor structure. Specifically, the Information Accuracy items (KI1, KI3, KI4) have very high uniqueness, indicating that the dimensions of accessibility and accuracy of digital information systems may be separate factors that are not well captured in this 5-factor structure.

Item SDM3 (work safety), which also has high uniqueness, indicates that the aspect of safety culture may be an independent dimension of human resources, separate from technical and interpersonal competencies.

**Discussion of Factor Structure**

The EFA results show a structure that is partly consistent and partly modified from the proposed theoretical construct. The comparison is as follows :

**Table 3**.9 Discussion of Factor Structure

| Theoretical Construct | Empirical Structure (EFA) | Conformity |
|---|---|---|
| Technical & Environmental Risk | Factor 1 (with KI2, KI5 loading negative) | ✓ Confirmed with modified |
| Distribution Efficiency | Factor 2 (ED1, ED2, ED4, ED5) | ✓✓ Confirmed very well |
| Operational Risk | Factor 3 (RO1, RO3, RO4, RO5) | ✓✓ Confirmed very well |
| Human Resources Risk | Split: Factor 4 (HR1, HR2) & Factor 5 (HR4, HR5) | ✓ Split into 2 dimensions |

| | | |
|---|---|---|
| Information Accuracy | Distributed: some in Factor 1, some with high uniqueness | ✗ Not confirmed as a separate factor |

Source : Processed by the author (2025)

Explanation of the table :

- HR risk is proven to be multidimensional. It is divided into technical-procedural dimensions (Factor 4) and interpersonal dimensions (Factor 5). This shows that HR competence in distribution cannot be viewed monolithically, but must be distinguished between hard skills and soft skills.
- Information Accuracy is not an independent factor. KI items are scattered and do not form a strong independent factor. Some items (KI2, KI5) are integrated with Technical Risk as a response mechanism, while other items (KI1, KI3, KI4) have high uniqueness. This indicates that the information system functions more as an enabler that supports other factors, rather than as an independent risk factor.
- Distribution Efficiency and Operational Risk are the most stable. These two constructs are very well confirmed, indicating that the theoretical conceptualization for these two dimensions is appropriate.

**Order of Factor Importance**

Based on the combination of maximum factor loading and proportion of variance explained, the order of importance of factors is :

**Table 3**.10 Order of Factor Importance

| Rank | Highest | Highest Load | Interpretation |
|---|---|---|---|
| 1 | Interpersonal Competence of Human Resources | 0.972 (HR5) | MOST CRITICAL |
| 2 | Distribution Efficiency | 0.861 (ED4) | Very Important |
| 3 | Operational Risk | 0.843 (OR4) | Very Important |
| 4 | Human Resource Compliance | 0.834 (HR1) | Important |
| 5 | Technical Risk | 0.732 (RT5) | Moderate |

Source : Author's own calculations (2025)

Although Factor 1 explains the most significant variance (10.5%), its value is less important because it is contextual and difficult to control. Meanwhile, Factor 5 (Human Resources), although it only accounts for 6.9% of the total variance, has a very high loading (0.972), indicating that it is the most important factor that can be modified by management.

**Discussion**

The results of Exploratory Factor Analysis (EFA) identified five main factors that cumulatively explained 40.5% of the variance, which is still within reasonable limits for social and managerial research involving complex latent constructs (Hair et al., 2019). Three constructs were consistently confirmed, namely Technical-Environmental Risk, Distribution Efficiency, and Operational Risk, while the Human Resource Risk construct was fragmented into two different dimensions, namely the technical-procedural dimension and the interpersonal dimension. Meanwhile, the Information Accuracy construct did not form as an independent factor, indicating that the information system plays a greater role as an enabling system rather than as an independent source of risk, in line with the view that information technology functions as a support for operational processes and decision making (DeLone & McLean, 2003).

The first factor, Technical–Environmental Risk (10.5% variance), shows a compensation mechanism, where information accuracy items (KI2 and KI5) have negative factor loadings. This indicates that when external conditions deteriorate, the need for communication and coordination becomes even more crucial to maintain distribution performance, as emphasized in the operational risk management literature (Tang, 2006). The second factor, Distribution Efficiency (8.2% variance), is characterized by the highest loading on the process speed indicator (ED4 = 0.861), which confirms that distribution efficiency is a multidimensional concept that depends not only on speed but also on process integration and resource management (Christopher, 2016). Furthermore, the third factor, Operational

Risk (7.7% variance), with the highest loading on administrative readiness (RO4 = 0.843), confirms that documentation and administrative readiness are the main foundations in ensuring the smooth operation of distribution (Slack et al., 2019).

The most significant finding in this study is the teamwork ability indicator (SDM5), which has the highest loading of 0.972 with a very low uniqueness value (0.005), indicating that team collaboration is the most crucial determinant in improving distribution efficiency. The separation of HR Risk into Factor 4 (Compliance and Technical Competence) and Factor 5 (Interpersonal Competence) confirms that human resource competence is multidimensional and needs to be differentiated between hard skills and soft skills, as stated in modern human resource management theory (Armstrong & Taylor, 2020).

The managerial implications of these findings for PT XYZ are significant. The top priority is to strengthen teamwork through regular team-building programs, a team performance-based reward system, and cross-functional job rotation. The next priority is to optimize operational systems through administrative digitization, the implementation of pre- departure checklists, and the use of real-time monitoring dashboards. In addition, procedural compliance needs to be strengthened through SOP refresher training, technology-based monitoring, and competency certification programs. Process speed can be improved through business process reengineering, the application of lean distribution principles, and the adoption of automation technology. Finally, external risk mitigation needs to be supported by early warning systems, contingency planning, and increased distribution fleet capabilities (Christopher, 2016; Slack et al., 2019).

However, this study has several limitations, including a marginal KMO value (0.491), which requires an increase in the sample size to at least 150 respondents, a relatively low explained variance value (40.5%), which indicates the presence of other unidentified factors, and the existence of several items with high uniqueness values that require instrument revision. Nevertheless, this study still makes an important contribution in revealing the latent factor risk distribution structure ( ) and provides clear and applicable guidelines for prioritizing managerial interventions to improve sugar distribution efficiency.

## 4. CONCLUSION

This study aims to identify risk factors that affect sugar distribution efficiency at PT. XYZ using the Exploratory Factor Analysis (EFA) method. Based on data analysis from 60 respondents, this study successfully extracted five main factors that explain 40.5% of the total data variance. Data feasibility tests show that even though the Kaiser-Meyer-Olkin (KMO) value is at the marginal limit (0.491), the data is still feasible for analysis. This was supported by a highly significant Bartlett's Test ($\chi^2 = 507.988$, $p < 0.001$) and a good Chi-Square Model Fit ($\chi^2 = 197.411$, $p = 0.253$), indicating that the extracted factor structure was statistically consistent with the observed data. The five factors that were successfully identified are :

1. Technical and Environmental Risk with Information Response (10.5% variance), which reflects the interaction between external conditions and the need for a responsive information system;
2. Distribution Efficiency (8.2% variance), which represents outcomes in the form of process speed, timeliness, customer satisfaction, and cost control;
3. Operational Risk (7.7% variance), which includes administrative readiness, error minimization, and route planning;
4. Human Resource Compliance and Technical Competence (7.2% variance), which focuses on SOP compliance and technological operating skills; and
5. Interpersonal Competence of Human Resources (6.9% variance), which emphasizes teamwork and responsibility.

The most significant finding was the identification of teamwork skills (HR5) as the most influential factor with the highest factor loading of 0.972 and uniqueness of 0.005. These results indicate that the ability of employees to collaborate effectively in cross- functional teams is the most crucial determinant for achieving distribution efficiency. Other important factors are administrative and documentation readiness (RO4, loading 0.843) and SOP compliance (SDM1, loading 0.834), which underscore the importance of an organized operational system and procedural discipline.

Based on the factor loading order, the hierarchy of factor importance is: Interpersonal Competence of Human Resources (0.972), Distribution Efficiency (0.861), Operational Risk (0.843), Compliance and Technical Competence of Human Resources (0.834), and Technical and Environmental

Risk (0.732). Although the technical-environmental factor explains the largest variance, its importance is relatively lower due to its contextual nature and difficulty in management control. In contrast, the HR and operational factors have very high loadings and can be directly intervened. This study also reveals that the HR Risk construct is multidimensional, divided into technical-procedural and interpersonal dimensions. Meanwhile, Information Accuracy did not emerge as an independent factor, indicating that the information system is more appropriately viewed as an enabler or moderator that supports other factors. Overall, this study confirms that the efficiency of sugar distribution at PT. XYZ is highly dependent on human factors, particularly the ability of human resources to work together in teams, followed by the quality of the operational system and procedural compliance.

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