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Developing operational risk-level assessment for selecting auditable units: Factor analysis and analytic hierarchy process approach

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ABSTRACT

This study introduces a new method for calculating operational risk levels in selecting audit units at the Central Bureau of Statistics (BPS). The key novelty of this study lies in its two-level assessment framework, which systematically compares different risk calculation methods to determine the most effective approach for operational risk evaluation. Using exploratory factor analysis, the study identifies four key operational risk factors: operational costs, internal control, investment and guarantees, and financial performance. The analytic hierarchy process (AHP) is then applied to systematically assign weight scores to these factors and their corresponding subcriteria based on expert judgment. Integrating these approaches results in a more structured, comprehensive, and accurate risk assessment model. Compared with the previous method, this new method shows a narrower but more optimal risk-level range, a slightly higher average operational risk level, and fewer cases of underestimation or overestimation. This new method enhances the precision of risk assessment in selecting BPS audit units, enabling the internal audit team to allocate resources more effectively by prioritizing high-risk work units. Consequently, the overall efficiency and effectiveness of BPS's internal audit process improve.

KEYWORDS:
Risk level; factor analysis; analytic hierarchy process; auditable unit; operational risk

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INTRODUCTION

Effective internal audit planning plays a crucial role in ensuring the optimal use of limited resources. With effective internal audit planning, the internal audit function can use limited resources wisely and efficiently, directing internal auditors' attention to areas that are critical and add value to the organization (Wang et al., 2021). According to Sudarmono and Tobing (2022), a risk-based audit plan is one approach in internal audit planning, which includes preparing a risk-based annual internal audit plan (PAITBR) that integrates the internal audit with the overall risk management framework of the organization in which the auditor operates (Institute of Internal Auditors, 2009).

One of the PAITBR process outcomes is a list of auditable units selected and organized based on their risk priority level. The list includes units requiring assurance and management system improvements (AAIPI, 2018). By determining the order of clients based on risk priority, the assignment is expected to generate improvement proposals that provide optimal added value and increase the effectiveness and efficiency of the organization's operations. Therefore, we can conclude that the selection of auditable units at Statistics Indonesia (Badan Pusat Statistik, BPS) is an activity to determine the priority of the work units (SATKER) in 34 BPS provinces and 480 BPS districts and cities that will be audited every year based on their priority level of risk. Thus, effective audit implementation can increase confidence that clients will achieve the established goals (AAIPI, 2018).

Organizations with different levels of risk management maturity require tailored approaches in selecting auditable units. According to Pusdiklatwas BPKP (2014), entities with a maturity level below 3 require oversight from the Government Internal Control Apparatus (APIP) and rely on a risk factor approach, while those with a maturity level above 3 can utilize a risk register for a pure risk-based internal audit. APIP plays a crucial role in strengthening risk management by ensuring that organizations with lower maturity levels implement structured risk assessments in their audit selection process. Despite BPS achieving a maturity score of 3.731 in 2022, its inspectorate still employs the risk factoring approach due to incomplete risk register data across its regional work units. This condition highlights the ongoing need for APIP to support and enhance risk-based auditing processes. The situation also aligns with previous research, which underscores challenges in fully implementing risk-based audits at BPS (Hariadi, 2020).

In calculating the risk level in selecting auditable units, the inspectorate of BPS still focuses on operational risk variables (Inspektorat Utama BPS, 2022) because assessing the level of operational risk used in selecting auditable units can enable auditors to focus on high-risk areas and allocate resources effectively (Zemtsov & Sorokin, 2022). Furthermore, a comprehensive operational risk-level assessment can identify vulnerabilities, exposures, and threats, minimizing risks and potential disruptions to business operations (Ebnöther et al., 2003; Lawrence et al., 2018; van Asseldonk & Velthuis, 2014).

Previous research by Hariadi (2020) revealed several weaknesses in the risk factor preparation method used by the BPS Inspectorate, particularly its failure to correctly apply the concept of risk factors (Pusdiklatwas BPKP, 2014). Currently, the BPS Inspectorate relies on a proxy approach, using operational risk variables without employing statistical techniques to classify them into proper operational risk factors. As a result, the method remains subjective (Hariadi, 2020). In principle, operational risk factors refer to characteristics, conditions, or sets of variables that increase the likelihood of operational risk (Wang et al., 2023). However, the data structure is tiered or multilevel (two levels), which adds complexity to risk assessment. Furthermore, the weighting of risk factor scores is highly subjective, as internal risk preferences influence it. The auditor's judgment, perception, and preferences determine the importance of each risk factor, causing the weighting system to vary annually (AAIPI, 2018). The variations in variables used in calculating risk levels are presented in Table 1.

Table 1. Differences of the Variable Used in the Risk-Level Calculation by Year

Variables	Score Weight		
	2021	2022	2023
IKPA value 2 years earlier	-	0.10	-
IKPA Value of the previous year	-	0.10	0.05
Previous Year Budget	-	0.05	-
Current Year Budget	-	0.10	-
Previous Year Capital Expenditure Budget	-	0.05	-
Current year capital expenditure budget	0.30	0.20	0.50
Current Year Goods Expenditure Budget	-	-	0.10
Current year Employee Expenditure Budget	-	-	0.05
Last year audited	0.50	0.30	0.10
Internal Control System (ICC) 2 years earlier	-	0.05	-
Internal Control System (SPI) 1 year earlier	0.20	0.05	0.20
Total	1.00	1.00	1.00

***Source**: The inspectorate of BPS*

The weaknesses of the auditable unit selection method currently used by the inspectorate of BPS will negatively affect the accuracy of operational risk level calculations. As a result, the selected audit unit sample may be less representative, leading to inefficient and ineffective allocation of audit resources (Felix et al., 2001). Auditors may spend too much time auditing low-risk areas and too little time on high-risk areas (Eilifsen & Messier, 2015). This situation is evidenced by testing the correlation between operational risk levels (as calculated by the BPS Inspectorate at the beginning of 2022) and the percentage of audit findings in 63 work units at the end of 2022 (as shown in Table 2). The result obtained a correlation value of 0.029 with a p-value of 0.82 (> 0,05), indicating no significant positive relationship between operational risk levels and audit findings. The results contradict several previous studies (Furqan et al., 2020; Setyaningrum, 2017; Siregar dan Rudiansyah, 2019), which found that higher operational risk levels tend to result in more audit findings.

In theory, audit units with a high-risk profile generally have more internal control weaknesses and noncompliance with applicable laws and regulations; therefore, auditors will find more errors, fraud, violations, and areas of improvement. However, the absence of a significant correlation in this case suggests potential flaws in the current risk assessment approach, emphasizing the need for more accurate risk factor classification and selection methods.

The correlation test results in Table 2 indicate that the current method for calculating operational risk in auditable unit selection used by the BPS inspectorate is still subjective and inadequate. Therefore, this finding highlights the urgent need for a new approach that is more objective and accurate in determining audit units' operational risk levels. In this way, the selection process can better prioritize actual operational risks, enhancing the effectiveness and efficiency of internal audit activities.

Table 2. Correlation Test Results Between Operational Risk Levels and Audit Findings

Variable		Percentage of Audit Findings 2022	Risk Level 2022
Percentage of Audit Findings 2022	Pearson Correlation	1	**0,029**
	Sig. (2-tailed)		0,820
	N	63	63
Risk Level 2022	Pearson Correlation	**0,029**	1
	Sig. (2-tailed)	0,820	
	N	63	63

Several previous studies (Yalisman, 2021; Purwanto et al., 2015; Valahzaghard & Ferdousnejhad, 2013; Wahyuningsih et al., 2022) proposed the use of factor analysis techniques and the analytic hierarchy process (AHP) to determine key risk factors and criteria score weights in auditable unit selection. Factor analysis helps identify key risk factors from a set of risk variables. This statistical technique can reduce the number of criteria or variables into several key factors representing all variables so that the data structure becomes tiered (2 levels) (Puslitbangwas BPKP, 2020). This approach aligns with several research results that discuss factor analysis to determine risk factors affecting internal audit activities' success, quality, and effectiveness (Almasria, 2022; Le & Nguyen, 2020; Mihret & Yismaw, 2007).

The AHP technique has been widely applied in cases and research related to risk assessment (Bognár & Benedek, 2022; Cerić & Ivić, 2023; Ristanović, 2023) because it can reduce some of the limitations of risk assessment techniques using probability and impact. AHP can provide consistency checks on subjective assessments, organize many risks into a structured framework, assist risk managers in making risk-related decisions, and provide a risk assessment process that is easy to understand and systematic (Sum, 2015). AHP can also be applied in internal audit planning, especially when selecting auditable units. Several previous studies (Demirhan et al., 2019; Kuvat & Kılıç, 2020; Sueyoshi et al., 2009; Sum, 2015; X. Wang et al., 2021, 2023) used the AHP method to assign weighted scores to the risk factors involved in internal audit planning. At the risk assessment stage, AHP helps weight audit criteria and subcriteria through pairwise comparisons between criteria. This weighting is based on expert judgment, thereby reducing auditor subjectivity.

Based on the problems above, this research develops new methods for calculating the level of operational risk that will be used in selecting auditable units in BPS. The new methods are based on risk factors obtained from the factor analysis results of all operational risk variables used by the inspectorate of BPS in determining the selection of auditable units. The weighting score is then given to each criterion and subcriterion in each risk factor that formed based on the AHP results. AHP is used as a multiplier factor for the level of operational risk in each variable that was determined and categorized first into an ordinal scale. Using the new method, which comprises two levels, the operational risk-level calculation results will be compared with the results of calculations from the BPS inspectorate using the old method, which comprises only one level. The comparison of the two methods distinguishes this research from several studies discussed previously. Therefore, the results can identify the most accurate, objective, and consistent method for calculating operational risk levels in auditable unit selection in all work units of Statistics Indonesia at the regency, city, and provincial levels.

RESEARCH METHOD

The stages carried out in this study consist of three phases of activity, as illustrated in Figure 1. The first phase is the formation of operational risk factors using factor analysis. The second phase involves weighing the criteria and subcriteria scores using AHP. The third phase includes preparing methods and calculating operational risk levels using the new methods.

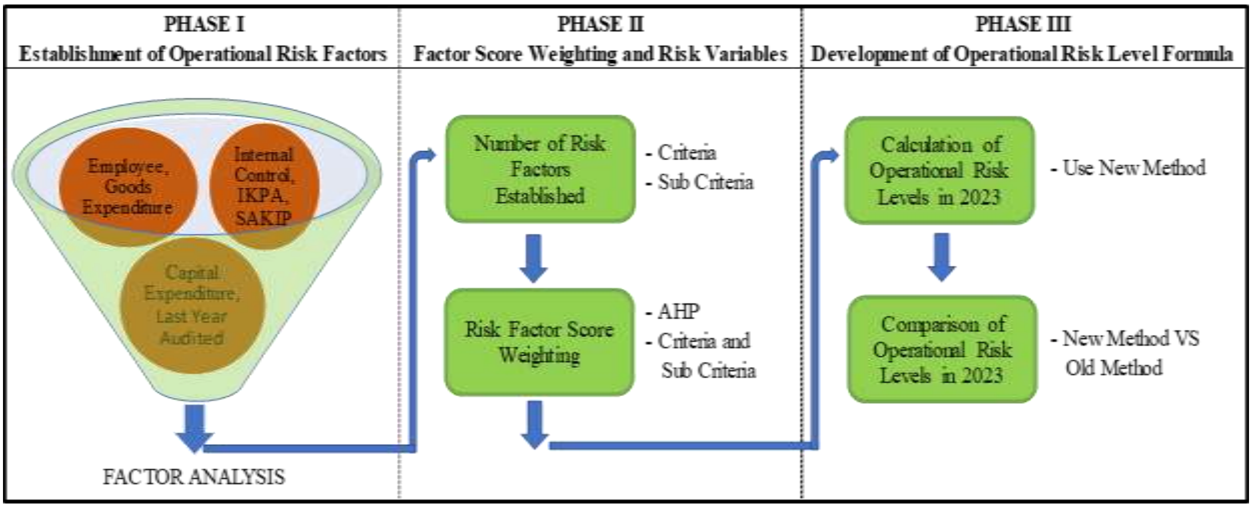

Figure 1. Conceptual Framework

Data Sources

This study utilizes two types of data sources: secondary and primary data. The secondary data was incorporated from various sources, specifically observational variables related to operational risk factors used by the BPS Inspectorate in selecting auditable units. These include budget implementation performance indicator (IKPA) value, the total budget for employees, goods and capital expenditures, the government agency performance accountability system (SAKIP) value, internal control system value, and the last year audited. Each variable is further described in the following section. The study utilizes data from the past two years for all variables except last year's audited variable, which is used to identify repeated or systemic findings (Lee, 1991). In total, 13 variables are analyzed to accommodate data from the last two years. The AHP method calculates operational risk factor score weights using primary data collected through questionnaires. This study's questionnaire was designed to collect respondents' preferences and assessments regarding the relevant risk factors from nine associate expert auditors at the BPS Inspectorate.

Budget Implementation Performance Indicator (IKPA)

According to Munawir and Meutia (2021), financial performance negatively relates to audit findings—the more problems or discrepancies in audit findings, the lower the quality of local government financial performance implementation. This finding aligns with Bakri and Rahardyan (2022), who showed that decreases in the effectiveness of local government financial management performance (not following proper procedures) relate to audit findings concerning noncompliance with laws and regulations. Thus, the lower the value of an agency's financial performance, the higher the level of operational risk owned by the work unit in BPS, characterized by the number of possible audit findings obtained if an internal audit is conducted. This is in line with the scoring of the operational risk level of each IKPA value category (Inspektorat Utama BPS, 2022), as shown in the Appendix. The lower the IKPA value achieved by a work unit in BPS, the higher the operational risk level received by the work unit.

Employee Expenditure, Goods Expenditure, and Capital Expenditure

Defitri (2020) showed that employee expenditure negatively influences a local government's financial independence level—the greater the amount of employee expenditure, the lower the local government's financial independence level. Therefore, local governments with low financial independence tend to have a higher risk of audit findings. This situation can occur due to limited financial capacity in funding personnel and operational expenditures, inefficient financial management due to dependence on transfer funds, and low budget discipline, which has the potential for irregularities. Saleh dan Rahadian (2023) found the same situation concerning goods and services expenditures, which are vulnerable to audit findings. The greater the expenditure on goods and services, the greater the risk of audit findings revealed by the auditor. This situation occurs due to the lack of completeness and accuracy of accountability for the expenditure of goods and services that do not match the actual evidence.

Furthermore, Rumihin et al. (2021) stated that capital expenditure positively influences the disclosure of errors in nonprofit organizations' financial statements. Capital expenditure management is very vulnerable, where many gaps can be exploited to commit acts of corruption because the capital expenditure budget is used to improve societal quality. The greater the capital expenditure, the more complex and challenging it is to account for it properly, thereby increasing the risk of irregularities that can reduce audit opinion. Furthermore, Qowi et al. (2017) showed that the larger the capital expenditure budget, the lower the local government performance score due to the high risk of moral hazard, where the parties involved can readily commit acts of corruption and nepotism. In this context, the capital expenditure budgeting process may experience budgetary slack, where the allocated budget does not reflect local capital expenditure's capacity or capability. As a result, local government performance is not optimal. Thus, the greater the amount of employee expenditure budget, goods and services expenditure, and capital expenditure, the higher the level of operational risk of a work unit in BPS, characterized by the number of possible audit findings obtained if an internal audit is conducted. This situation is in line with the scoring of operational risk-level criteria for each category of the amount of expenditure budget ceiling (Inspektorat Utama BPS, 2022), as shown in Appendix 1. The greater the expenditure budget ceiling of a work unit in BPS, the higher the operational risk-level score will be received by the work unit.

Value of Government Agency Performance Accountability System (SAKIP)

Lukito (2014) found that to gain public trust, the government must build accountability by transparently reporting development performance to the public. By reporting clear and open performance, the government can demonstrate its responsibility in developing tasks and programs. Similarly, Hendrik Latief et al. (2023) said that if a region achieves performance accountability achievements in the good or very satisfactory category (with a SAKIP achievement value above 60), the region can be said to effectively and efficiently implement budget programs and activities. The above indicates that the lower the performance accountability score obtained by a government agency, the higher the risk of failure in implementing the program and activity budget effectively and efficiently. This situation aligns with previous studies (Fresiliasari, 2023; Masni & Sari, 2023; Saraswati & Triyanto, 2020), showing that agencies that can account for their performance accountability well tend to be better able to prevent or reduce the level of risk of corruption or fraud from a program or activity in the agency.

Previous studies (Ditasari & Sudrajat, 2020; Rasyid et al., 2022) found a negative relationship between local government performance accountability and the risk level of BPK audit findings. This suggests that weaker performance accountability correlates with higher audit risks. Based on these findings, it can be inferred that a lower SAKIP score in a BPS work unit indicates a higher operational risk level, as reflected in the potential number of audit findings if an internal audit is conducted.

Internal Control System

Additional research (Fresiliasari, 2023; Kustiawan, 2017; Ladewi et al., 2020; Manfa, 2022) showed that an organization or company with a suitable internal control system would significantly help prevent the risk of fraud or fraud committed by employees or management. In other words, the better the internal control system in an organization, the less risk there is of fraud. Furthermore, Widodo and Sudarno (2017) indicated that the weaker the internal control system in a local government, the more risk of audit findings related to internal control and noncompliance with laws and regulations, which ultimately results in a poor BPK audit opinion received (reputational risk). The theories from the research above suggest that the weaker the internal control system owned by a work unit in BPS, the higher the level of operational risk in the work unit, characterized by the number of possible audit findings obtained if an internal audit is conducted. This aligns with the scoring of operational risk-level criteria from each category of the internal control system (Inspektorat Utama BPS, 2022), as shown in Appendix 1. The weaker the internal control system of a work unit in BPS, the higher the operational risk level received by the work unit.

Last Year Audited

The existing literature (Arens et al., 2014; Sueyoshi et al., 2009) highlights that the time elapsed since the last audit is a key audit risk factor. A longer period increases the likelihood of material misstatements in financial statements or violations of laws and regulations. Accordingly, in BPS work units, a longer gap since the last audit indicates a higher operational risk level, reflected in the potential number of audit findings during an internal audit. This aligns with the BPS Inspectorate's operational risk-level scoring criteria (Inspektorat Utama BPS, 2022), as shown in Appendix 1, where a longer audit gap results in a higher operational risk score.

Factor Analysis

This study employs two analytical techniques: factor analysis and the Analytical Hierarchy Process (AHP). This analysis uses exploratory factor analysis because no theoretical basis or previous research provides a definitive framework for applying risk factors in operational risk-level calculations (Rahim & Saputra, 2018). Thus, this study aims to develop a new theoretical model. Additionally, factor analysis structures the data into a multilevel format (two levels): level 1 is operational risk factors (criteria), and level 2 is operational risk variables (subcriteria). This study's operational risk factors were formed through four stages below.

1. Factor analysis feasibility test. According to Yamin and Kurniawan (2011), factor analysis can be feasible or suitable to be applied as a research model if the results of the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (MSA) test in measuring sample adequacy show a KMO value greater than 0.5. Bartlett's Test of Sphericity results were used to see if the correlation matrix is not an identity matrix with the condition that the significance value must be less than 0.05. Another mandatory test is checking the anti-image matrix correlation's MSA value to assess each variable's feasibility. Variables with an MSA value of less than 0.5 are eliminated.

2. Factor extraction. It is a process to determine the number of factors formed using the eigenvalue and scree test approaches (Hair et al., 2018). Factors with eigenvalues greater

than one are retained as significant factors. A scatter plot is used to visualize the decrease in eigenvalues and determine the number of factors that formed.

3. Variable distribution and factor rotation. At this stage, the distribution of variables into the factors formed based on the loading factor value is conducted. Factor rotation ensures that all operational risk variables can be optimally distributed among the n operational risk factors formed. This research uses the orthogonal method recommended by experts because it produces a factor structure that is simpler and easier to interpret than the oblique method (Johnson & Wichern, 2005).
4. Operational risk factor naming. The next step is to give names to the operational risk factors formed. Each risk factor is given a name that reflects the characteristics of the operational risk variables that form it.

Meanwhile, the AHP was carried out in four steps.

1. Define the problem and establish a hierarchy. The hierarchy includes objectives, criteria, subcriteria, and alternatives (Muanley et al., 2022).
2. Compile a pairwise comparison matrix C. The pairwise comparison matrix is prepared by assessing the relative importance of elements at each level of the hierarchy. As proposed by Saaty (1980), the assessment is done using a scale of 1–9.

$$C = \left[C_{ij}\right]^{nxn} = \begin{bmatrix} 1 & C_{12} & \dots & C_{1n} \\ 1/C_{12} & 1 & \dots & C_{2n} \\ . & . & . & . \\ 1/C_{1n} & 1/C_{2n} & . & 1 \end{bmatrix} \quad \dots\dots\dots (1)$$

where C is the pairwise comparison matrix of criteria, c_{ij} is the comparison ratio between criterion i and criterion j, and n is the number of criteria.

$$\text{NoC} = \frac{n(n-1)}{2} \quad \dots\dots\dots (2)$$

where NoC is the number of pairwise comparisons the decision maker must conduct.

3. Calculate the eigenvalue (λ) and eigenvector (W). The priority vector (W) or weights are calculated using the geometric mean method of each row of the pairwise comparison matrix (Saaty, 1980). The priority vector is normalized so that the sum becomes one.

$$C \text{ x } W = \lambda_{max} \text{ x } W \quad \dots\dots\dots (3)$$

$$GM_i = \left[\prod_{j-1}^{n} C_{ij}\right]^{1/n} \quad \dots\dots\dots (4)$$

where GMi is the geometric mean value of criterion i.

$$W_i = \frac{GM_i}{\sum_{i-1}^{n} GM_i} \quad \dots\dots\dots (5)$$

4. Calculate the alternative score by multiplying the criteria priority vector by the alternative score against each criterion. The result is each alternative's global score.
5. Check for consistency. The AHP method requires consistency in judgment, which is checked by calculating the consistency ratio (CR). The judgment is considered consistent if the CR is less than 0.1.

RESULT AND DISCUSSION

Phase 1: Establishment of Operational Risk Factors

The factor analysis results indicate that none of the 13 operational risk variables were eliminated. This outcome was obtained from a series of tests to ensure the feasibility of the data in conducting further factor analysis. First, the KMO MSA and Bartlett's Test of Sphericity were conducted. The test results showed a KMO value of 0.732 >0.5 and Bartlett's Test significance value of 0.000 <0.05, which indicated that the data qualified for factor analysis. Furthermore, testing was conducted on each operational risk variable using anti-image matrix correlation to examine the MSA value. The results showed that all 13 operational risk variables had MSA values >0.5, suggesting that the variables are feasible and can be analyzed further. Additional testing on the communality value was also conducted to ensure that the operational risk variables could explain the factors well. The results showed that all variables had communality values >0.5, indicating a strong relationship between the operational risk variables and the factors to be formed.

After establishing feasibility, the following process is factor extraction to determine the number of operational risk factors that will be formed. In this study, the number of factors was determined using two methods, namely the scree plot and the percentage of diversity (eigenvalue) approach. The scree plot shows that the curve starts to slope after four components or factors are formed, which indicates that four factors are the ideal number of dominant operational risk factors. The eigenvalue approach also confirms these results, forming four factors with an eigenvalue >1 and can explain 66.447% of the total variance in the data—the result of the factor extraction completely presented in Table 3.

Table 3. Factor Extraction Results

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	Variant %	Cumulative %	Total	Variant %	Cumulative %	Total	Variant %	Cumulative %
1	3.748	28.831	28.831	3.748	28.831	28.831	3.245	24.960	24.960
2	2.190	16.845	45.676	2.190	16.845	45.676	2.201	16.931	41.891
3	1.618	12.448	58.124	1.618	12.448	58.124	1.833	14.097	55.988
4	1.082	8.323	66.447	1.082	8.323	66.447	1.360	10.459	66.447
5	0.823	6.327	72.774						
6	0.773	5.945	78.720						
7	0.642	4.935	83.655						
8	0.623	4.792	88.447						
9	0.484	3.726	92.173						
10	0.475	3.657	95.830						
11	0.365	2.807	98.638						
12	0.116	0.891	99.528						
13	0.061	0.472	100.000						

After determining the number of factors, the next step is distributing the 13 operational risk variables to the four identified factors. Variable distribution is based on the highest loading factor value of each variable. Orthogonal rotation was applied to achieve a more apparent factor structure. Each of the four operational risk factors was named according to the characteristics of the variables that composed them, as shown in Table 4. The first risk factor, which explained 28.831% of the variance, was named "operational costs" and comprised the goods and employee expenditure ceiling variables. The second risk factor, which explained 16.845% of the total variance, was named "internal control" and consists of SAKIP and SPI score variables. The third risk factor, which explained 12.448% of the total variance, was named "investment and assurance" and comprised the capital expenditure ceiling variable and the last year audited. Finally, the fourth risk factor, which explained 8.323% of the total variance, was named "financial performance" and comprised the IKPA score variable.

Table 4. Naming the Formed Operational Risk Factors

Risk Factor Name	Total Variance	Risk Variable Items	Loading Factor
Risk Factors 1:	28.831	Goods Expenditure Budget for 2022	0.890
Operational costs		Goods Expenditure Budget for 2023	0.884
		Employee Expenditure Budget for 2022	0.868
		Employee Expenditure Budget for 2023	0.863
Risk Factors 2:	16.845	SAKIP scores in 2021	0.724
Internal control		SAKIP scores in 2022	0.711
		Internal Control System in 2021	0.666
		Internal Control System in 2022	0.663
Risk Factors 3:	12.448	Capital Expenditure Budget for 2023	0.742
Investment and Assurance		Capital Expenditure Budget for 2022	0.719
		Last Year Audited	−0.704
Risk Factors 4:	8.323	IKPA Value in 2021	0.821
Financial performance		IKPA Value in 2022	0.661

Based on the four identified operational risk factors, a multilevel data structure (2 levels) can be developed to calculate operational risk levels for selecting auditable units in BPS. The first level (criteria) represents the four main operational risk factors: operational costs, internal control, investment and assurance, and financial performance. The second level (subcriteria) consists of operational risk variables that comprise each risk factor. In this multilevel data structure, each risk factor and risk variable can be given different weights or priorities depending on their importance and needs for the organization. Furthermore, the operational risk level of each work unit can be calculated using the AHP method. By implementing this structured approach, the selection of auditable units in BPS becomes more systematic and comprehensive, ensuring that all relevant operational risk aspects are effectively considered (Bhushan & Rai, 2004; Wang, 2021).

Phase 2: Weighting of Criteria and Subcriteria Scores

Based on the factor analysis results, four main operational risk factors are used as criteria for selecting auditable units in BPS: operational costs, internal control, investment and assurance, and financial performance. After weighting these criteria using the AHP method (Table 5), the highest weight is assigned to investment and assurance (0.343), followed by operational costs (0.284), internal control (0.223), and financial performance (0.150). At the subcriteria level, the capital expenditure budget 2023 holds the highest weight (0.1960) under the investment and assurance category. This outcome aligns with previous studies (Qowi et al., 2017; Rumihin et al., 2021), which found that investment management (capital expenditure) is a significant operational risk factor in the public sector. High capital expenditure can increase risks such as irregularities in procurement, inefficiency, and potential corruption.

The second highest-weighted subcriterion is the 2023 goods expenditure (0.1612), categorized under operational costs. This finding aligns with Saleh and Rahadian (2023), who identified operational costs, including goods expenditure, as a key risk factor in public sector operational risk management. High operational costs (including goods expenditure) can lead to risks such as waste, inefficiency, and potential irregularities. The third highest-weighted subcriterion is the last year audited (0.1092), which falls under investment and assurance. This result supports prior research (Arens et al., 2014; Sueyoshi et al., 2009), which emphasizes that the elapsed since the last audit is an audit risk factor to which auditors must pay attention. The longer the interval, the higher the likelihood of material misstatements in the client's financial statements or noncompliance with laws and regulations.

Table 5. Total Score Weight in Each Operational Variable

Risk Factor (Criteria)	Criteria Score Weight	Risk Variable (Sub Criteria)	Sub Criteria Score Weight	Total Score Weight (Criteria x Sub Criteria)	Rank
Operational costs	0.284	Goods Expenditure Budget for 2022	0,127	0,0361	10
		Goods Expenditure Budget for 2023	0,568	0,1612	2
		Employee Expenditure Budget for 2022	0,059	0,0167	13
		Employee Expenditure Budget for 2023	0,246	0,0700	7
Internal control	0.223	SAKIP scores in 2021	0,148	0,0328	11
		SAKIP scores in 2022	0,368	0,0820	5
		Internal Control System in 2021	0,121	0,0269	12
		Internal Control System in 2022	0,363	0,0808	6
Investment and Assurance	0.343	Capital Expenditure Budget for 2023	0,571	0,1960	1
		Capital Expenditure Budget for 2022	0,111	0,0379	9
		Last Year Audited	0,318	0,1092	3
Financial performance	0.150	IKPA Value in 2021	0,281	0,0423	8
		IKPA Value in 2022	0,719	0,1081	4

The score weighting results indicate that investment and assurance—particularly capital expenditures and audit frequency—are the top priorities when selecting auditable units at BPS. Furthermore, the operational cost aspect, especially the management of goods expenditures, plays a crucial role in mitigating operational risk. By considering the weighted score of each criterion and subcriterion, BPS can calculate the operational risk level using a structured, two-level framework. This approach enables the BPS Inspectorate to allocate audit resources more effectively and precisely prioritize auditable units.

Phase 3: New Method Development and Operational Risk-Level Calculation in 2023

The first stage of this study involves grouping operational risk variables using factor analysis, forming four operational risk factors so that the data structure formed becomes two levels. Level 1 is an operational risk factor (criteria), and level 2 is an operational risk variable (subcriteria). In the second stage, the weighting process is applied to each risk factor (criteria) at level 1 and risk variable (subcriteria) at level 2 using the AHP. The results of the weighted scores of the criteria and subcriteria obtained are then used as a multiplier factor in preparing the operational risk-level method for selecting auditable units, as illustrated in Figure 2.

Referring to Figure 2, the new methods for calculating the level of operational risk can generally be formulated as follows:

New Operational Risk-Level Calculation Formula = $\sum_{i=1}^{n} W_i \sum_{j=1}^{m} W_{ij} T_{ij}$ .... (6)

$= \{W_1{*}(W_{11}{*}T_{11}) + W_1{*}(W_{12}{*}T_{12}) + W_1{*}(W_{13}{*}T_{13}) + W_1{*}(W_{14}{*}T_{14})\} + \{W_2{*}(W_{21}{*}T_{21}) + W_2{*}(W_{22}{*}T_{22}) + W_2{*}(W_{23}{*}T_{23}) + W_2{*}(W_{24}{*}T_{24})\} + \{W_3{*}(W_{31}{*}T_{31}) + W_3{*}(W_{32}{*}T_{32}) + W_3{*}(W_{33}{*}T_{33})\} + \{W_4{*}(W_{41}{*}T_{41}) + W_4{*}(W_{42}{*}T_{42})\}$

$= \{0{,}284 * (0{,}127 * T_{11}) + 0{,}284 * (0{,}568 * T_{12}) + 0{,}284 * (0{,}059 * T_{13}) + 0{,}284 * (0{,}246 * T_{14})\} + \{0{,}223 * (0{,}148 * T_{21}) + 0{,}223 * (0{,}368 * T_{22}) + 0{,}223 * (0{,}121 * T_{23}) + 0{,}223 * (0{,}363 * T_{24})\} + \{0{,}343 * (0{,}571 * T_{31}) + 0{,}343 * (0{,}111 * T_{32}) + 0{,}343 * (0{,}318 * T_{33})\} + \{0{,}150 * (0{,}281 * T_{41}) + 0{,}150 * (0{,}719 * T_{42})\}.$

The final formulation of the new methods for calculating the level of operational risk in the selection of *auditable units* in BPS can be obtained as follows:

$= \{(0{,}0361 * T_{11}) + (0{,}1612 * T_{12}) + (0{,}0167 * T_{13}) + (0{,}07 * T_{14})\} + \{(0{,}0328 * T_{21}) + (0{,}0820 * T_{22}) + (0{,}0269 * T_{23}) + (0{,}0808 * T_{24})\} + \{(0{,}1960 * T_{31}) + (0{,}0379 * T_{32}) + (0{,}1092 * T_{33})\} + \{(0{,}0423 * T_{41}) + (0{,}1081 * T_{42})\}.$

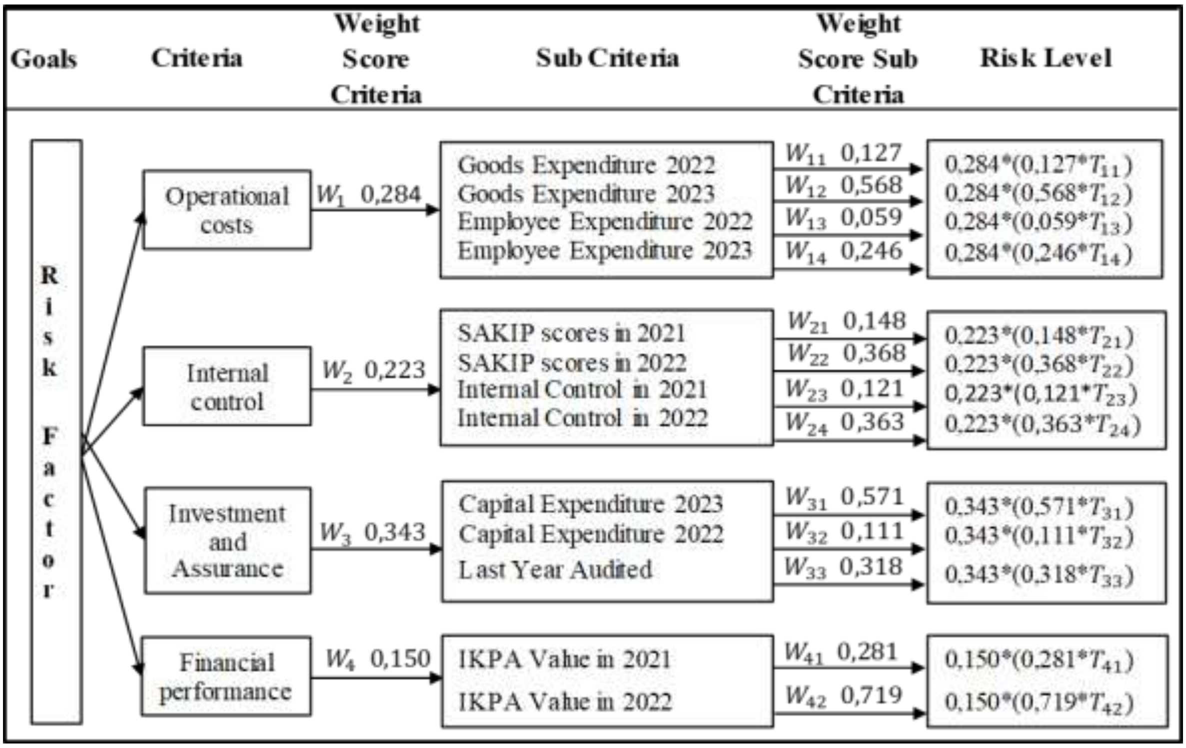

Figure 2. Development Process of a New Method of Operational Risk-Level Calculation in Audit Unit Selection

Meanwhile, the formula for calculating the level of operational risk that the BPS inspectorate has used based on the old method (described in Figure 3) through the formula:

Old Operational Risk-Level Calculation Formula = $\sum_{i=1}^{n} W_i\, T_i$ .... (7)

Where n is four operational risk factors formed, W_i is the weight score of criteria on the i-th operational risk factor, m is the number of risk variables in each operational risk factor, W_{ij} is the weighted score of subcriteria on the i-th operational risk factor and j-th operational risk variable, T_{ij} is the risk-level score for the i-th operational risk factor and j-th operational risk variable.

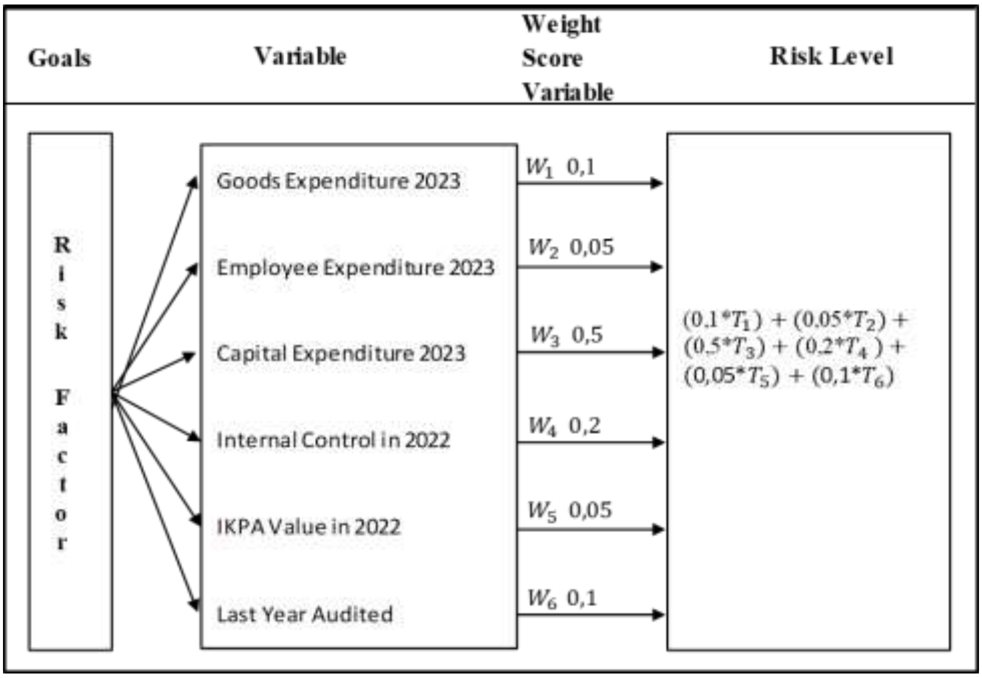

Figure 3. Development Process of an Old Method of Operational Risk-Level Calculation in Audit Unit Selection

The calculation results of the operational risk level range in 34 provincial BPS work units and 480 regency or city BPS work units using the new method (3.066–1.142) are narrower than the range of values in the old method (3.55–1) as shown in Table 6. A narrower range of values may affect the accuracy of the operational risk level. Furthermore, a narrower range of operational risk-level values may indicate that the new method assesses the operational risk level more clustered around the middle value. According to Hubbard (2020), an excessively narrow range can obscure critical data variability and introduce bias, while an overly broad range can also cause difficulty in discerning the true level of risk.

Therefore, an optimal range of values is essential to ensure an accurate assessment of risk levels and to distinguish risk levels well. A value range that is too narrow or too wide can lead to errors in identifying risks and allocating resources for risk mitigation. Hubbard (2020) suggested that the ideal or optimal range of risk-level values is 10th to 90th percentiles. This range is broad enough to capture data variability but not extreme. Therefore, in the case of operational risk levels in the selection of auditable units at BPS, according to (Hubbard, 2020), the ideal operational risk-level value range is between values 2 (30th–40th percentiles) and 3 (50th–70th percentiles). This range is broad enough to capture data variability and operational risks that may occur, but it is not so extreme that it can cause bias in assessing operational risk levels.

A value of 1 (10th–20th percentiles) may indicate an outlier or an excessively low operational risk level, while a value of 4 (80th–90th percentiles) suggests an outlier or an overly high-risk level. Therefore, neither value is ideal for reference in risk assessment. According to Aven (2016), extreme maximum or minimum values can lead to overestimation or underestimation of the operational risk level, leading to errors in decision-making and resource allocation. Therefore, the assessment of operational risk using the new method is more optimal for application to the selection of auditable units in BPS when viewed in terms of the range of values produced compared to the old method. The new method does not produce extreme or outlier values (1 or 4) compared to the old method, which produces the lowest value, which is too low (1).

Table 6. Descriptive Statistics of Operational Risk Levels in 2023

Scope	Minimum		Maximum		Average	
	New Method	Old Method	New Method	Old Method	New Method	Old Method
BPS- Province	1,1420	1	3,0657	3,55	1,9680	1,8066
BPS- Regency/city	1,5535	1,25	3,0295	2,95	2,1101	1,8941
All BPS Office	1,1420	1	3,0657	3,55	1,9774	1,8124

The data in Table 6 shows that the average level of operational risk in all BPS work units using the new method is 1.9774, slightly higher than that of the old method of 1.8124. This difference is seen more clearly in the BPS regency/city, where the average level of operational risk using the new method is 2.1101 higher than the old method of 1.8941. This disparity can occur because the new method uses the AHP method in calculating the level of operational risk, and the weighting of scores on risk factors (criteria) and operational risk variables (subcriteria) is carried out in stages (2 levels). The use of the AHP method in a 2-level manner can lead to an increase in the average level of operational risk in the new methods for several reasons. First, the assessment is conducted more comprehensively, resulting in a more accurate assessment of operational risk and reflecting the actual conditions, which can lead to a higher average risk level (Dey, 2003). Second, using the AHP method allows each operational risk factor and operational risk variable to be given different weights according to their level of importance. A higher weight on certain risk factors or variables can increase the average risk level (Saaty, 1980). Third, the AHP method allows for consistent assessments using a pairwise comparison matrix, reducing bias and inconsistency in risk-level assessment that may occur in other methods. Therefore, the results of risk-level assessment can increase in accuracy, and the average risk level can rise (Russo & Camanho, 2015).

The calculation results of operational risk levels in the new and old methods are categorized into four groups: very low (risk level < 1.5), low (1.5 ≤ risk level < 2), high (2 ≤ risk level < 3), and very high (risk level ≥ 3). Table 7 highlights an underestimation of operational risk levels when using the old methods. For instance, several work units previously classified in the "very low" category under the old methods shifted to the "low" category (73 work units) and even to the "high" category (4 work units) after applying the new methods. This outcome indicates that the new AHP and multilevel risk assessment methods enhance the identification of risk factors that may have been overlooked. A shift in the category of operational risk level (underestimation) also occurred in work units initially classified as "low" under the old methods, with 139 work units moving to the "high" category after applying the new methods.

Table 7. Number of Work Units in Provincial and Regency/City BPS Based on Changes in Operational Risk-Level Categories in 2023

Risk Category		New Method				Total
		Very Low	Low	High	Very High	
Old Method	Very Low	58	73	4	0	135
	Low	1	114	139	0	254
	High	0	14	87	1	102
	Very High	0	0	19	4	23
Total		59	201	249	5	514

Furthermore, Table 7 shows cases of overestimating operational risk-level calculations using the old methods. For example, some work units that previously used the old methods were in the "high" category but shifted to the "low" category (14 work units) after using the new methods. The change in the category of operational risk level that occurs after using the new method shows cases of underestimation or overestimation of the calculation of the operational risk level. These cases negatively affect the accuracy of selecting the sample of work units to be conducted in internal audits. The sample of selected BPS provincial and regency/city work units may be less representative, which may result in auditors spending too much time, money, and effort auditing low-risk areas and too little time, money, and effort on high-risk areas (Eilifsen & Messier, 2015).

The adoption of new methods incorporating a multilevel risk assessment approach (2 levels) with the AHP enables a more accurate and comprehensive evaluation of each work unit's operational risk level. This aligns with Bhushan and Rai (2004), who posited that using the AHP method in risk assessment has the advantage of accommodating various criteria and subcriteria in a structured manner and providing appropriate priority weights. This approach enhances the accuracy and comprehensiveness of risk assessments. Furthermore, Wang (2021) emphasized the importance of risk assessment methods that account for uncertainty and ambiguity in data. The study proposed using multilevel risk assessment methods to handle complexity in risk assessment. As used in the new methods, the multilevel risk assessment method can provide more accurate risk-level assessment results and consider various operational risk factors and variables more in-depth and comprehensively. Consequently, this approach allows the BPS Inspectorate to allocate internal audit resources more effectively, prioritizing work units with higher operational risk levels, thus increasing the efficiency and effectiveness of the internal audit process at BPS.

Proving the Accuracy of the New Method Compared to the Old Method in Calculating Operational Risk Levels in 2023

The data presented in Tables 8 and 9 show a significant difference in the average value of risk variables according to the operational risk-level categories between the old and new methods. Table 8, which applies the old method, reveals certain irregularities and inconsistencies with established theories and prior research. One notable inconsistency appears in the "very high" operational risk-level category, where the average employee expenditure for 2022 and 2023, goods expenditure for 2022 and 2023, and capital expenditure for 2022 are lower than those in the "high" and "low" risk-level categories. This finding contradicts the theoretical expectation that higher operational expenditures—such as employee, goods, and capital expenditures—correlate with higher operational risk levels (Defitri, 2020; Qowi et al., 2017; Saleh & Rahadian, 2023). This irregularity indicates an error in calculating the operational risk level using the old method.

Table 8. Average Value of Risk Variables by Operational Risk-Level Category in 2023 using the Old Method

Risk Variables	Operational Risk-Level Category			
	Very Low	Low	High	Very High
Employee Expenditure 2022	3,210,215,029.63	4,243,143,893.70	4,521,130,068.63	3,357,867,304.35
Employee Expenditure 2023	3,166,332,244.44	4,269,053,799.21	4,552,737,931.36	3,367,900,391.30
Goods Expenditure 2022	6,649,104,570.37	13,175,580,929.13	11,320,077,333.33	13,020,585,304.35
Goods Expenditure 2023	6,010,082,407.41	11,594,559,314.96	9,379,366,754.89	11,042,962,043.48
Capital Expenditure 2022	307,512,118.52	75,684,743.08	367,571,558.82	237,477,608.70
Capital Expenditure 2023	1,918,585.19	2,808,149.61	568,914,627.45	3,387,071,913.04
IKPA 2022	95.53	94.35	94.02	93.99
IKPA 2021	96.53	95.92	94.97	96.12
SPI 2021	2.76	2.82	2.64	2.43
SPI 2022	3.90	3.38	3.09	2.87
Last Year Audited	2.77	3.26	3.40	3.70
SAKIP 2021	64.22	62.74	63.44	60.84
SAKIP 2022	69.95	68.20	68.25	66.26

In contrast, Table 9, which applies the new method, demonstrates consistency with the established theory. The average employee expenditure budget for 2022 and 2023, goods expenditure budget for 2022 and 2023, and capital expenditure budget for 2022 and 2023 are increasing as the operational risk-level category rises from "very low" to "very high." This result aligns with theoretical expectations and previous research, which suggest that higher operational expenditures—such as employee, goods, and capital expenditures—correlate with a higher level of operational risk within an organization.

Table 9. Average Value of Risk Variables by Operational Risk-Level Category in 2023 using the New Method

Risk Variables	Operational Risk-Level Category			
	Very Low	Low	High	Very High
Employee Expenditure 2022	2,615,362,288.14	3,561,138,437.81	4,586,311,172.69	7,487,422,000.00
Employee Expenditure 2023	2,594,542,169.49	3,535,744,810.95	4,626,855,698.79	7,557,146,400.00
Goods Expenditure 2022	4,876,410,898.31	7,200,138,487.56	15,337,215,469.88	28,889,058,400.00
Goods Expenditure 2023	4,536,777,576.27	6,725,555,248.76	13,020,800,654.61	21,075,376,400.00
Capital Expenditure 2022	112,749,644.07	201,194,420.00	189,146,995.98	1,925,589,000.00
Capital Expenditure 2023	502,457.63	45,239,482.59	445,086,831.33	3,390,964,600.00
IKPA 2022	96.39	95.28	93.72	87.43
IKPA 2021	97.04	96.48	95.17	95.53
SPI 2021	2.85	2.65	2.81	3.00
SPI 2022	3.88	3.51	3.28	3.00
Last Year Audited	2.93	3.08	3.31	3.60
SAKIP 2021	64.98	63.39	62.59	63.10
SAKIP 2022	71.02	68.94	67.73	67.91

In the old method (Table 9), the average SAKIP value decreases as the operational risk-level category increases but exhibits inconsistency in the "high" category. In contrast, the new method (Table 10), the average SAKIP value tends to decrease consistently along with the increase in the operational risk-level category from "very low" to "very high." This outcome indicates that the SAKIP value as a risk variable in the new method aligns more closely with established theories and prior research, which indicate that lower performance accountability (SAKIP) corresponds to higher operational risk in a work unit (Ditasari & Sudrajat, 2020; Rasyid et al., 2022). SPI 2021 and IKPA 2021 variable values in the old (Table 9) and new methods (Table 10) show a fluctuating pattern; thus, no conclusion can be drawn regarding which is better.

However, the average value of SPI 2022 and IKPA 2022 show that both the old and new methods provide the same pattern—the average value of SPI 2022 and IKPA 2022 consistently decreases along with the increase in the operational risk-level category from "very low" to "very high." This outcome indicates that the data on the risk variables of the SPI 2022 and IKPA 2022 values in the old and new methods are consistent with previous theories and research: the lower the value of the SPI and IKPA of a work unit (SATKER) at BPS, the higher the level of operational risk in the work unit (SATKER) (Bakri & Rahardyan, 2022; Widodo & Sudarno, 2017). In the risk variable for the last year audited, the data on the old and new methods provide results that are equally consistent with previous theories and research. The average last year audited increased along with the operational risk category from "very low" to "very high." This finding is consistent with the theory that states that the longer a work unit is not audited, the higher the level of operational risk (Arens et al., 2014; Sueyoshi et al., 2009).

The discussion results indicate that the risk variables in the new method align more consistently with established theories and prior research, making it a more accurate and reliable approach for calculating operational risk levels in selecting auditable units at BPS. By adopting this improved method, BPS can more precisely identify high-risk work units, allowing for a more targeted allocation of audit resources and risk mitigation efforts. This, in turn, enhances the overall effectiveness and efficiency of operational risk management within the BPS environment. This outcome supports the theory expressed by Moeller (2009), which states that accurate risk assessment is the key to success in implementing risk-based auditing. If the risk assessment is inaccurate, the prioritization of audit units can be misdirected, so audit resources are not allocated effectively and efficiently.

CONCLUSION

This study successfully developed a new method for calculating operational risk levels in selecting auditable units at BPS by integrating factor analysis and AHP. Through factor analysis, this study identified and formed four main operational risk factors: operational costs, internal control, investment and monitoring, and financial performance. Establishing these risk factors allows the data structure to be multilevel, with risk factors as criteria and risk variables as subcriteria. Furthermore, applying the AHP method, weighted scores are assigned to each criterion and subcriteria systematically and consistently based on expert judgment. By combining these approaches, the new method offers a more structured and data-driven framework for assessing operational risk levels. Compared to the old methods, the new methods have several significant advantages.

First, the new method produces a narrower but more ideal or optimal range of operational risk-level values. This range of values is wide enough to capture data variability and operational risks that may occur but not too extreme to avoid bias in assessing risk levels. Second, the average operational risk level using the new method is slightly higher than the old method, indicating that the new method can provide a risk-level assessment that better reflects actual conditions. Third, new methods allow more accurate identification of operational risk levels, thereby reducing underestimation or overestimation of risk levels in the old methods. This ability is critical to ensuring the proper allocation of audit resources and avoiding wasting resources on low-risk areas or inattention to high-risk areas.

By integrating the AHP approach with a multilevel risk assessment (2 levels), the new methods provide a more accurate and comprehensive operational risk assessment. This enables the BPS Inspectorate to allocate internal audit resources more effectively, prioritizing work units with higher operational risk levels. In this way, the overall effectiveness and efficiency of the internal audit process in BPS can be increased. Additionally, this method can be applied by agencies without an existing risk register, enhancing the accuracy of audit unit selection based on key risk factors.

This study has several limitations that should be addressed in future studies. First, the observation variables used in this study are limited to BPS internal data, excluding external risk factors that may also influence operational risk. Second, the weighting of scores using AHP is carried out based on subjective assessments from middle auditors, which can be influenced by individual bias and experience. Third, the study focuses solely on operational risk assessment for selecting auditable units, without addressing other aspects of risk management. Future research can enhance the model by incorporating external risk factors, such as economic, political, and regulatory conditions, for a more comprehensive analysis. Additionally, exploring more objective and data-driven weighting methods, such as entropy weighting, can reduce subjectivity in risk evaluation. Lastly, future works can expand the scope of research, such as weighting the scores of each risk contained in the risk register.

REFERENCES

AAIPI. (2018). *Pedoman perencanaan audit berbasis risiko auditor intern pemerintah Indonesia*. Asosiasi Auditor Intern Pemerintah Indonesia.

Almasria, N. A. (2022). Factors affecting the quality of audit process "The external auditors' perceptions." *The International Journal of Accounting and Business Society, 30*(1), 107-148. https://doi.org/10.21776/ijabs.2022.30.1.539

Arens, A. A., Elder, R. J., & Beasley, M. S. (2014). *Auditing and assurance service: An integrated approach*. Pearson Education Inc.

Aven, T. (2016). Risk assessment and risk management: Review of recent advances on their foundation. *European Journal of Operational Research, 253*(1), 1-13. https://doi.org/10.1016/j.ejor.2015.12.023

Bakri, M. R., & Rahardyan, T. M. (2022). Pengaruh opini, temuan dan karakteristik daerah terhadap kinerja keuangan provinsi jambi. *Jurnal Akuntansi, 10*(1), 1-14. https://doi.org/10.26460/ja.v11i1.2990

Bhushan, N., & Rai, K. (2004). *Strategic decision making: Applying the analytic hierarchy process*. Springer.

Bognár, F., & Benedek, P. (2022). A novel AHP-PRISM risk assessment method—An empirical case study in a nuclear power plant. *Sustainability, 14*(17), 11023. https://doi.org/10.3390/su141711023

Cerić, A., & Ivić, I. (2023). Application of analytic hierarchy process (AHP) in earthquake risk assessment. *Proceedings of the 2nd Croatian Conference on Earthquake Engineering - 2CroCEE* (pp. 964-974). https://doi.org/10.5592/CO/2CroCEE.2023.133

Defitri, S. Y. (2020). Pengaruh belanja modal dan belanja pegawai terhadap tingkat kemandirian keuangan daerah. *Fokus Bisnis: Media Pengkajian Manajemen Dan Akuntansi, 19*(2), 107-119. https://doi.org/10.32639/fokusbisnis.v19i2.476

Demirhan, A., Oktay, S., & Atasoy, T. (2018). Audit firm selection using an analytic hierarchy process and an application. In H. Kapucu & C. Akar (Eds.), *Changing organizations: From the psychological & technological perspectives*. IJOPEC Publication.

Dey, P. K. (2003). Analytic hierarchy process analyzes risk of operating cross-country petroleum pipelines in India. *Natural Hazards Review, 4*(4), 213–221. https://doi.org/10.1061/(asce)1527-6988(2003)4:4(213)

Ditasari, R. A., & Sudrajat, M. A. (2020). Pengaruh opini audit dan temuan audit BPK terhadap kinerja pemerintah daerah pada kabupaten/kota di provinsi jawa timur. *Inventory: Jurnal Akuntansi, 4*(2), 104. https://doi.org/10.25273/inventory.v4i2.7668

Ebnöther, S., Vanini, P., Mcneil, A., & Antolinez-Fehr, P. (2003). Modelling operational risk. *Journal of Risk, 5*(1), 1-16. https://doi.org/10.2139/ssrn.293179

Eilifsen, A., & Messier, W. F. (2015). Materiality guidance of the major public accounting firms. *Auditing: A Journal of Practice & Theory, 34*(2), 3-26. https://doi.org/10.2308/ajpt-50882

Yalisman, F. (2021). Analisis prioritas monitoring dan evaluasi pelaksanaan anggaran kementerian negara/lembaga berdasarkan model analityc hierarchy process. *Jurnal Ilmiah Mahasiswa FEB Universitas Brawijaya, 7*(2), 18.

Felix, W. L., Gramling, A. A., & Maletta, M. J. (2001). The contribution of internal audit as a determinant of external audit fees and factors influencing this contribution. *Journal of Accounting Research, 39*(3), 513-534. https://www.jstor.org/stable/2672973

Fresiliasari, O. (2023). Pengaruh sistem pengendalian intern pemerintah dan kompetensi aparatur pemerintah desa terhadap pencegahan fraud dalam pengelolaan dana desa dengan akuntabilitas sebagai variabel intervening. *Jurnal Akuntansi Dan Pajak, 23*(2), 1-10. http://jurnal.stie-aas.ac.id/index.php/jap

Furqan, A. C., Wardhani, R., Martani, D., & Setyaningrum, D. (2020). The effect of audit findings and audit recommendation follow-up on the financial report and public service quality in Indonesia. *International Journal of Public Sector Management, 33*(5), 535-559. https://doi.org/10.1108/ijpsm-06-2019-0173

Hariadi, B. W. (2020). Analisis perencanaan audit intern berbasis risiko pada inspektorat utama badan pusat statistik. *ABIS: Accounting and Business Information Systems Journal, 8*(1). https://doi.org/10.22146/abis.v8i1.58883

Latief, H., Asri, S., & Santosa, A. (2023). Akuntabilitas kinerja instansi pemerintah pada pemerintah kabupaten paser. *Journal Publicuho, 5*(4), 1367-1376. https://doi.org/10.35817/publicuho.v5i4.83

Hubbard, D. W. (2020). *The failure of risk management*. Wiley.

Inspektorat Utama BPS. (2022). *Program Kerja Pengawasan Tahunan (PKPT) inspektorat utama tahun 2022*.

Institute of Internal Auditors. (2009). *IIA position paper: The role of internal auditing in enterprise-wide risk management*. The Institute of Internal Auditors. https://na.theiia.org/standards-guidance/Public Documents/PPTheRoleofInternalAuditinginEnterpriseRiskManagement.pdf

Johnson, R. A., & Wichern, D. W. (2005). *Multivariate analysis. In: Encyclopedia of statistical sciences*. Wiley.

Hair, J. F., Black, J., Babin, W. C., Anderson, B. J., & R. E. (2018). *Multivariate data analysis*. Cengage Learning.

Kustiawan, M. (2017). Pengaruh pengendalian intern dan tindak lanjut temuan audit terhadap kualitas laporan keuangan yang berimplikasi terhadap pencegahan fraud. *Jurnal Akuntansi, 20*(3), 345-362. https://doi.org/10.24912/ja.v20i3.2

Kuvat, Ö., & Kılıç, B. İ. (2020). The evaluation of the criteria for the selection and change of the independent audit firm using the AHP method. *Contemporary Studies in Economic and Financial Analysis, 102*, 189-202. https://doi.org/10.1108/s1569-375920200000102015

Ladewi, Y., Nurhayati, N., Mizan, M., & Janatul, R. (2020). Pengaruh penerapan sistem pengandalian internal pemerintah terhadap pencegahan kecurangan. *Kajian Akuntansi, 21*(1), 99-107. https://doi.org/10.29313/ka.v21i1.5835

Lawrence, A., Minutti-Meza, M., & Vyas, D. (2018). Is operational control risk informative of financial reporting deficiencies?. *Auditing, 37*(1), 139-165. https://doi.org/10.2308/ajpt-51784

Le, T. T., & Nguyen, T. M. A. (2020). The adoption of risk-based audit approach in the independent audit firms: A study of a case of Vietnam. *The Journal of Asian Finance, Economics and Business, 7*(2), 89-97. https://doi.org/10.13106/jafeb.2020.vol7.no2.89

Lee, R. M. (1991). Auditing as pattern recognition: Automated analysis of documentary procedures. http://dx.doi.org/10.2139/ssrn.2025707

Lukito, P. K. (2014). *Membumikan transparansi dan akuntabilitas kinerja sektor publik: tantangan berdemokrasi ke depan*. Grasindo.

Manfa, A. G. (2022). Pengaruh audit internal dan pengendalian internal terhadap pencegahan kecurangan (studi empiris amal usaha Muhammadiyah tingkat kota Pekanbaru). *ECOUNTBIS: Economics, Accounting and Business Journal, 2*(3), 521–530. https://jom.umri.ac.id/index.php/ecountbis/article/view/113

Masni, E. P., & Sari, V. F. (2023). Pengaruh akuntabilitas, kesesuaian kompensasi, pengendalian internal, dan budaya organisasi terhadap kecurangan dana desa. *Jurnal Eksplorasi Akuntansi, 5*(1), 263-277. https://doi.org/10.24036/jea.v5i1.729

Mihret, D. G., & Yismaw, A. W. (2007). Internal audit effectiveness: An Ethiopian public sector case study. *Managerial Auditing Journal, 22*(5), 470-484. https://doi.org/10.1108/02686900710750757

Moeller, R. R. (2009). *Brink's modern internal auditing a common body of knowledge* (7th ed.). John Wiley & Sons.

Muanley, Y. Y., Son, A. L., Mada, G. S., & Dethan, N. K. F. (2022). Analisis sensitivitas dalam metode analytic hierarchy process dan pengaruhnya terhadap urutan prioritas pada pemilihan smartphone android. *VARIANSI: Journal of Statistics and Its Application on Teaching and Research, 4*(3), 173–190. https://doi.org/10.35580/variansiunm32

Munawir, M., & Meutia, R. (2021). Faktor-faktor yang mempengaruhi kinerja keuangan: Studi kasus kabupaten/kota di aceh. *Jurnal Ilmiah Mahasiswa Ekonomi Akuntansi (JIMEKA), 6*(4), 1. https://doi.org/10.24815/jimeka.v6i4.19751

Purwanto, P., Hartoyo, D. S., & S. (2015). Net neutrality in India. *International Journal of Science and Research (IJSR), 4*(12), 217-222. https://doi.org/10.21275/v4i12.nov151590

Pusdiklatwas. (2014). *Perencanaan penugasan audit intern*. BPKP.

Qowi, R., & Prabowo, T. J. W. (2017). Pengaruh karakteristik pemerintah daerah dan temuan pemeriksaan bpk terhadap kinerja pemerintah daerah kabupaten/kota di indonesia tahun anggaran 2012. *Diponegoro Journal of Accounting, 6*(1), 1-13. http://ejournal-s1.undip.ac.id/index.php/accounting

Rahim, A., & Saputra, H. (2018). Exploratory factor analysis (EFA) pada penyerapan anggaran pendapatan dan belanja negara (APBN) tahun 2017 di provinsi sumatera barat. *Indonesian Treasury Review: Jurnal Perbendaharaan Keuangan Negara Dan Kebijakan Publik, 3*(3), 236-254. https://doi.org/10.33105/itrev.v3i3.72

Rasyid, Y., Suci, R. G., & Putri, A. M. (2022). Pengaruh opini audit dan temuan audit bpk terhadap kinerja pemerintah daerah kabupaten/kota di provinsi Riau. *PROMOSI (Jurnal Pendidikan Ekonomi), 10*(2), 80-93. https://doi.org/10.24127/pro.v10i2.6589

Ristanović, V., Primorac, D., & Mikić, M. (2023). Application of multi-criteria assessment in banking risk management. *Zagreb International Review of Economics and Business, 26*(1), 97-117. https://doi.org/10.2478/zireb-2023-0005

Rumihin, R., Ahuluheluw, N., & Leiwakabessy, T. F. F. (2021). Pengaruh karakteristik pemerintah daerah terhadap opini audit atas laporan keuangan pada kab/kota di Provinsi Maluku Tahun 2016-2018. *Prosiding Conference on Economic and Business Innovation (CEBI), 1*(1), 990–1002. Retrieved from https://jurnal.widyagama.ac.id/index.php/cebi/article/view/167

Russo, R. D. F. S. M., & Camanho, R. (2015). Criteria in AHP: A systematic review of literature. *Procedia Computer Science, 55*, 1123-1132. https://doi.org/10.1016/j.procs.2015.07.081

Saaty, T. L. (1980). *The analytic hierarchy process*. Hill International Book Company.

Saleh, I., & Rahadian, Y. (2023). Akar Masalah Tidak Tercapainya Opini WTP: Studi Kasus di Pemerintah Daerah XX. *Indonesian Treasury Review: Jurnal Perbendaharaan, Keuangan Negara Dan Kebijakan Publik, 8*(2), 109-124. https://doi.org/10.33105/itrev.v8i2.547

Saraswati, S. R., & Triyanto, D. N. (2020). Pengaruh Temuan Audit, Transparansi, dan Akuntabiltas terhadap Tingkat Korupsi (Studi pada Pemerintah Daerah Jawa Timur Tahun 2015-2018). *E-proceeding of Management, 7*(1), 1000-1007.

Setyaningrum, D. (2017). The Direct and mediating effects of an auditor's quality and the legislative's oversight on the follow-up of audit recommendation and audit opinion. *International Journal of Economic Research, 14*(13), 269-292.

Siregar, M. I., & Rudiansyah, J. (2019). Pengaruh jumlah temuan audit terhadap opini audit kabupaten/kota se sumatera. *Jurnal Ecoment Global, 4*(1), 101-124. https://doi.org/10.35908/jeg.v4i1.576

Sudarmono, S., & Tobing, A. N. L. (2022). Designing a risk-based internal audit plan in the internal auditor division (a case study in PT. XY). *Budapest International Research and Critics Institute-Journal (BIRCI-Journal), 5*(1), 1528-1542.

Sueyoshi, T., Shang, J., & Chiang, W. C. (2009). A decision support framework for internal audit prioritization in a rental car company: A combined use between DEA and AHP. European *Journal of Operational Research, 199*(1), 219-231. https://doi.org/10.1016/j.ejor.2008.11.010

Sum, R. M. (2015). Risk prioritization using the analytic hierarchy process. AIP Conference Proceedings.

Valahzaghard, M. K., & Ferdousnejhad, M. (2013). Ranking insurance firms using AHP and Factor Analysis. *Management Science Letters, 3*, 937-942. https://doi.org/10.5267/j.msl.2013.01.027

van Asseldonk, M. A. P. M., & Velthuis, A. G. J. (2014). Risk-based audit selection of dairy farms. *Journal of Dairy Science, 97*(2), 592-597. https://doi.org/10.3168/jds.2013-6604

Wahyuningsih, T., Ristono, A., & Muhsin, A. (2022). The application of factor analysis (FA) in evaluating supplier selection criteria in PT. Wijaya Karya Beton Tbk and ranking suppliers using the integration of analytical hierarchy process (AHP) and adaptive ratio assessment (ARAS). *Technium: Romanian Journal of Applied Sciences and Technology, 4*(6), 11-17. https://doi.org/10.47577/technium.v4i6.6814

Wang, L. (2021). A multi-level fuzzy comprehensive assessment for supply chain risks. *Journal of Intelligent & Fuzzy Systems, 41*(4), 4947-4954. https://doi.org/10.3233/jifs-189981

Wang, X., Ferreira, F. A. F., & Yan, P. (2023). A multi-objective optimization approach for integrated risk-based internal audit planning. *Annals of Operations Research, 1*(1), 30. https://doi.org/10.1007/s10479-023-05228-2

Wang, X., Zhao, T., & Chang, C.-T. (2021). An integrated FAHP-MCGP approach to project selection and resource allocation in risk-based internal audit planning: A case study. *Computers & Industrial Engineering, 152,* 107012. https://doi.org/10.1016/j.cie.2020.107012

Widodo, O. P., & Sudarno. (2017). Pengaruh temuan kelemahan sistem pengendalian intern dan temuan ketidakpatuhan terhadap ketentuan peraturan perundang-undangan. *Diponegoro Journal of Accounting, 6*(1), 1-9.

Yamin, S., & Kurniawan, H. (2011). *SPSS complete: Teknik analisis statistik terlengkap dengan software SPSS*. Salemba Infotek.

Zemtsov, T. A., & Sorokin, M. A. (2022). Risk assessment in risk-oriented audits by internal audit units. Vestnik Tomskogo Gosudarstvennogo Universiteta. *Ekonomika, 57*, 129-144. https://doi.org/10.17223/19988648/57/9

APPENDICES

Appendix 1. Observation Variables and Categorization

Observation Variable	Category Score	
	Risk Variable	Risk Level
IKPA Value in 2021 and 2022	1. IKPA Value < 70 2. 89 > IKPA Value ≥ 70 3. 95 > IKPA Value ≥ 89 4. IKPA Value ≥ 95	4. Very High 3. High 2. Low 1. Very Low
Employee Expenditure Budget for 2022 and 2023	1. Budget Value < IDR 3 billion 2. IDR 3 billion ≤ Budget Value < IDR 4 billion 3. IDR 4 billion ≤ Budget Value < IDR 5 billion 4. Budget Value ≥ IDR 5 billion	1. Very Low 2. Low 3. High 4. Very High
Goods Expenditure Budget for 2022 and 2023	1. Budget Value < IDR 5 billion 2. IDR 5 billion ≤ Budget Value < IDR 7,5 billion 3. IDR 7,5 billion ≤ Budget Valueu < IDR 12 billion 4. Budget Value ≥ IDR 12 billion	1. Very Low 2. Low 3. High 4. Very High
Capital Expenditure Budget for 2022 and 2023	1. Budget Value < IDR 50 million 2. IDR 50 million ≤ Budget Value < IDR 200 million 3. IDR 200 million ≤ Budget Value < $IDR\ 1\ billion$ 4. Budget Value u ≥ IDR 1 billion	1. Very Low 2. Low 3. High 4. Very High
Internal Control System in 2021 and 2022	1. The internal control system is considered inadequate 2. The internal control system is less than adequate 3. The internal control system is adequate enough 4. The internal control system is very adequate	4. Very High 3. High 2. Low 1. Very Low
Last Year Audited	1. Audited in the previous 1 year n−1 2. Audited in the previous 2 years n−2 3. Audited in the previous 3 years n−3 4. Audited in the previous 4 or more years, n−4, n−5, etc	1. Very Low 2. Low 3. High 4. Very High
SAKIP scores in 2021 and 2022	1. SAKIP Score < 50 2. 50 ≤ SAKIP Score < 60 3. 60 ≤ SAKIP Score < 70 4. SAKIP Score ≥ 70	4. Very High 3. High 2. Low 1. Very Low

Source: *The Ministry of Finance and Inspektorat Utama BPS, 2022*