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An Integrated Framework for MRO Risk Mitigation Beyond Single Dimension Classification in The Upstream Oil and Gas Sector

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ABSTRACT

Upstream oil and gas companies face simultaneous MRO inventory stockouts and overstock, reflecting misallocation rather than resource scarcity. Existing classification methods – ABC (value), VED (criticality), and ADI-CV (demand pattern) – each address only one dimension, leaving residual risk that an integrated framework can eliminate. This study applies a combined ABC-VED-ADI-CV approach to 90 MRO items at an Indonesian upstream company using 12 months of transactional data and structured expert interviews. ABC identified Class A (6% of items with 80% of cost); VED classified 54% as Vital; ADI-CV found 96% exhibiting lumpy demand, confirming that conventional forecasting is inappropriate for virtually the entire portfolio. Integrating all three dimensions identified three tubing items as highly critical – Class A, Vital, and Lumpy – whose stockout triggers immediate well shutdown. The framework offers practitioners a replicable prioritisation tool for procurement, safety stock, and supplier management.

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INTRODUCTION

The oil and gas industry contributes significantly to the country's energy security. There are two main components to this sector's operations, including upstream and downstream. Exploring and producing oil and gas reserves is part of the upstream industry, which necessitates complex and costly operating procedures. To keep things operating smoothly, the equipment and supporting infrastructure must be reliable. Any interruptions, particularly those related to the availability of supplies and equipment, can result in significant downtime, thereby affecting output and operating efficiency in the field [1].

In Indonesia, upstream production facilities experienced unscheduled downtime, with MRO-related supply problems cited as a main contributing factor, underscoring the strategic significance of dependable inventory management [2], [3]. MRO materials, which include spare parts, consumables, and maintenance supplies that keep equipment running but are not part of the finished product, are essential for keeping operations running in this field [3], [4]. In practice, MRO inventory management in upstream oil and gas industries is quite complex. Companies routinely manage thousands of different MROs with varying demand, lead times, and operational significance [5]. Inadequate management leads to two opposing but equally detrimental outcomes: stockouts of vital supplies, which halt production, and overstocking of non-critical products, which tie up capital, consume warehouse space, and increase obsolescence risk [4], [6]. An initial study at Indonesia upstream company located in Java showed that just 33 of 90 MRO items (37%) were managed optimally, with 36 items (40%) experiencing stockout conditions and 24 items (27%) in overstock during 2024. These data translate into actual operational risks: crucial material shortages can paralyze production lines, whilst excess inventory of low-priority items ties up cash that could be used more profitably. This dual-failure pattern demonstrates that the real issue is not resource scarcity, but rather misallocation caused by the lack of a systematic, multidimensional classification framework. As a result, inventory management requires an organized approach. This includes categorizing products based on their importance using the VED (Vital, Essential, Desirable) technique, as well as their value and frequency of use using the ABC (Always Better Control) method [7].

VED classifies materials and spare parts by their importance to production and operations. This technique classifies materials and spare parts components into three categories: Vital, Essential, and Desirable [8]. The Vital (V) category includes spare parts that are vital and could halt production if they are unavailable. The Essential (E) category contains spare parts that, if unavailable, could result in financial loss for the company. The Desirable (D) category comprises spare parts that do not disrupt production. The fundamental advantage of the VED analysis is its ability to categorize material criticality, allowing for the refinement of procurement strategies and inventory management [9]. One simple technique for determining the importance of a spare part is to estimate how much it impacts the product's quality and how much money the company could lose if it is unavailable. The greater production losses occur when a spare item is absent, the more critical it is [10]. A recent study found that the fraction of goods classified as Vital and Essential accounts for the majority of drug expenditures. This shows that the VED technique effectively allocates finances and inventory management to the most necessary commodities, avoiding stockouts and assuring the availability of key supplies [7]. Another research also demonstrated that this strategy is equally applicable in the oil and gas business, integrating VED analysis with replenishment schedules based on criticality levels. Their findings confirm that VED classification can reduce the number of spare parts in inventory while maintaining operational reliability, as inventory management methods can be focused on critical components that directly impact production downtime [11].

Always Better Control (ABC) categorization is a common approach for sorting products based on their value and relevance to improve inventory control [12]. This technique improves inventory management by making resource allocation easier and allowing monitoring and control to be altered based on each item's value and frequency of use [8]. The ABC analysis approach divides inventory into three categories. Category A accounts for approximately 20% of total item units but 80% of total inventory value. Category B represents approximately 30% of total item units and 15% of total inventory value. Category C accounts for roughly half of the total number of items, but just 5% of the inventory value [13]. This technique saves money on storage costs by tracking overstock and ensuring that safety stock levels are always optimal [7]. Several recent studies have increased the practical significance of this strategy. A recent study emphasized that ABC remains an important method in spare parts classification and management due to its ability to simplify inventory by focusing on high-value commodities [14]. Research showed that employing ABC in industrial warehouses reveals that just approximately 15% of things (class A) account for more than 75% of total inventory value, whereas more than 60% of items (class C) account for only about 5%. This means that control efforts can be directed towards class A [15].

Another problem that upstream oil and gas companies have when managing MRO stocks is that MRO demand planning is not always correct. MRO demand planning is frequently incorrect since the need for MRO materials varies and might be intermittent, lumpy, irregular, or smooth, depending on time, equipment, and operational activities. If it does not determine what is wrong with this condition, it may result in overstocking, stockouts, unnecessary storage costs, and production disruption. Forecasting approaches and inventory management tactics that work well for commodities with stable demand will fall short for things with irregular or rapidly variable demand. Differences in demand intervals and demand quantity variety have a significant impact on demand prediction accuracy.

The Average Demand Interval - Coefficient of Variation (ADI-CV) technique is one of the most widely used methods for grouping MRO demand patterns with intermittent demand characteristics. In this method, ADI represents the average time between requests for an item, indicating how frequently it is requested. If the ADI value is higher, it indicates that the item is used less frequently, implying that demand is erratic. The CV (Coefficient of Variation) indicates how much the demand amounts differ from the average. A high CV value indicates that demand is changeable and unpredictable, whereas a low CV value indicates that demand is rather steady. By combining these two measures, ADI-CV categorizes demand patterns into four types: smooth (high frequency and low variability), erratic (high frequency but high variability), intermittent (low frequency but low variability), and lumpy (low frequency with high variability) [16]. This segmentation is critical since each group requires a unique method for inventory management and forecasting purposes. Exponential smoothing is better for things with consistent demand, whereas bootstrapping or Croston-based techniques are better for items with variable demand [17], [18]. Therefore, ADI-CV is not only a tool for determining what consumers desire, but it can also be used to make strategic inventory management decisions, particularly in highly complex industries such as oil and gas, mining, and heavy manufacturing. According to a recent study, using ADI-CV improves demand forecasting precision and reduces the risk of overstocking and stockouts for commodities with irregular demand. For example, A research used ADI-CV in an agent-based manufacturing system to manage demand fluctuation for spare components [16]. Hong et al., in their research, also said that ADI-CV is effective in detecting unusual patterns in spare parts demand that are not usually present [17]. It is critical for enhancing the accuracy of forecasting models that deal with non-constant demand patterns. As a result, research found that ADI-CV has emerged as a significant instrument for controlling spare parts inventory in industries characterized by high unpredictability, such as the upstream oil and gas sector [18].

Recent research has examined various techniques of classifying MRO inventories, showing both their advantages and disadvantages, as detailed in Table 1. The ABC technique is still widely used for prioritizing high-value commodities and simplifying inventory control, with recent improvements including fuzzy and multi-criteria variations to improve decision accuracy [19], [20]. The VED method is increasingly being used to assess item criticality, particularly in contexts where downtime risk is high, such as healthcare and manufacturing, with findings indicating that identifying critical components allows for more resilient inventory strategies [8], [21]. Meanwhile, the ADI-CV classification has gained popularity for dealing with irregular and sporadic demand patterns, where traditional forecasting frequently fails, as evidenced by recent research demonstrating its ability to map demand states and improve spare parts planning in uncertain conditions [16], [22], [23]. Together, these studies highlight that while ABC, VED, and ADI-CV each give diverse perspectives—economic value, criticality, and demand behaviour, respectively—relying on a single method delivers only partial insight

Despite the obvious complementarity of ABC, VED, and ADI-CV, the existing literature reveals a significant gap. While dual-method integrations, particularly ABC-VED, have been investigated in healthcare [7], [24] and manufacturing [25], [26], the simultaneous integration of all three dimensions has not been rigorously applied in the upstream oil and gas MRO context. While ABC, VED, and ADI-CV each capture only one risk dimension — economic value, operational criticality, or demand unpredictability, respectively — their simultaneous integration uniquely identifies items that are concurrently high-cost, operationally vital, and subject to lumpy demand, thereby enabling precision-targeted inventory control that no single-method or dual-method approach can achieve. This study addresses this gap by developing and implementing an integrated ABC–VED–ADI CV classification framework for 90 MRO items at an Indonesian upstream oil and gas company. The primary contribution is methodological. By incorporating all three dimensions simultaneously, the framework identifies highly critical MRO items – those with high economic value, operational dependability, and unpredictable demand – as the highest-priority targets for stringent inventory control. The findings have practical consequences for procurement strategy, safety stock policy, and supplier management, and provide a reproducible paradigm that may be applied to other complex MRO situations.

Table 1. The comparison of the inventory classification method

ASPECT	ABC	VED	ADI-CV
Basis of classification	Annual consumption value	Operational criticality	Demand pattern
Primary strength	Enables cost-focused prioritization and resource allocation	Captures operational risk beyond monetary value	Identifies irregular and lumpy demand patterns objectively
Key weakness	Ignores criticality and demands unpredictability	Ignores the cost and demand pattern	Ignores economic value and operational criticality
Stockout risk awareness	Low	High	Moderate
Overstock risk awareness	Moderate	Low	Moderate
Residual risk if used alone	High – misses critical low-cost and lumpy-demand items	High – misses costly and demand-volatile items	High – misses high-value and operationally vital items

RESEARCH METHOD

The study was conducted at one of Indonesia's upstream oil and gas companies, specifically in Java. The study's population included all 90 active MRO material types managed in the warehouse from January to December 2024, representing the complete number of the company's active MRO inventory. This ensured that classification results reflected the full scope of the company's inventory management challenge without the sampling bias that would result from partial selection.

Two types of data were collected. Secondary data, covering the period January to December 2024, was collected from the company's Enterprise Resource

Planning (ERP) system and comprised material descriptions and specifications, monthly demand records, demand frequency, and unit pricing. The 12-month data window was chosen to cover the whole yearly cycle of maintenance activities, ensuring that seasonal or project-driven demand trends were well captured. These data provided the foundation for the ABC and ADI-CV analyses. Primary data were obtained to assess each material's operational criticality, which served as the input for the VED classification. Primary data were obtained through structured interviews with the company's Inventory Controller, a senior warehouse expert with over 10 years of experience and direct knowledge of material functions and their operational implications. The interview procedure was designed around a validated criticality assessment matrix [27], which addressed two dimensions: (1) the functional role of each material in the manufacturing process (supporting, safety- critical, or irreplaceable in main production equipment), and (2) the impact of material unavailability on production continuity (no impact, quality loss, productivity reduction, or unexpected machine stoppage). To reduce subjectivity, interview responses were cross-validated against maintenance work orders, production disruption logs, and equipment failure records stored in the company's database. Any discrepancies between the interviewee's assessment and the objective records were addressed during a follow-up discussion session.

The data analysis was conducted in five sequential stages. Stage 1 - ABC analysis: annual usage value was computed for each item (unit price x total annual demand). Items were ranked from highest to lowest usage value, cumulative value percentages were calculated, and Class A (cumulative top 80%), Class B (next 15%), and Class C (remaining 5%) designations were assigned according to standard Pareto-based thresholds [28], [29], [30].

Stage 2 – VED Analysis: Each item was classified into Vital (V), Essential (E), or Desirable (D) categories using the criticality matrix in Table . The matrix assigns items to one of six groups based on the intersection of functional role and production impact; Groups 5-6 correspond to Vital, Groups 3-4 to Essential, and Groups 1-2 to Desirable [27], [31].

Stage 3 – ABC-VED Matrix: A 3x3 ABC-VED matrix was constructed to integrate the cost and criticality dimensions, yielding three management categories: Category I (subclasses AV, AE, AD, BV, CV – requiring the highest management priority), Category II (BE, BD, CE – moderate priority), and Category III (CD – lowest priority) [7], [14], [32].

Table 2. Critical assessment criteria and VED group assignment

CATEGORY	GROUP	CRITERIA (FUNCTION X IMPACT)
Desirable	1	Function: supporting equipment (no direct production impact). Impact: unavailability has no impact on production.
	2	Function: operator safety. Impact: unavailability has no impact on production.
Essential	3	Function: supporting equipment. Impact: unavailability reduces production volume.
	4	Function: operator safety or main equipment.

CATEGORY	GROUP	CRITERIA (FUNCTION X IMPACT)
		Impact: unavailability causes quality loss or production reduction.
Vital	5	Function: main production equipment or operator safety.
		Impact: unavailability leads to a significant production reduction.
	6	Function: main production equipment.
		Impact: unavailability causes a sudden machine stoppage and complete shutdown.

Stage 4 – ADI-CV Analysis: Demand patterns were characterised using two statistics computed from the monthly demand series. The ADI represents the average number of months between non-zero demand occurrences as calculated using (1), whereas the CV can be calculated using (2) [16].

$$ADI = \frac{\sum_{N}^{i=1} t_i}{N} \quad (1)$$

$$CV = \frac{\sqrt{\frac{\sum_{i=1}^{N} (\varepsilon_i - \varepsilon)^2}{N}}}{\varepsilon} \quad (2)$$

$$\varepsilon = \frac{\sum_{i=1}^{N} \varepsilon_i}{N} \quad (3)$$

The classification thresholds ADI = 1.32 and CV = 0.49 were established by Syntetos and Boylan (20) and subsequently validated in multiple industrial studies [16], [22], [33], [34], [35]. Items with ADI>1.32 and CV > 0.49 are classified as Lumpy; ADI ≤ 1.32 and CV>0.49 as Erratic; ADI>1.32 and CV ≤0.49 as Intermittent; and ADI≤1.32 and CV ≤0.49 as Smooth.

Stage 5 – Integration and Prioritisation. The final stage combined all three analyses to identify highly critical MRO materials, defined as items simultaneously classified as A (high economic value), Vital (high operational criticality), and exhibiting a Lumpy or Erratic demand pattern (high forecast uncertainty). This combination represents the highest level of inventory risk, including large financial exposure, operational indispensability, and forecasting difficulty, and thus warrants the most stringent control policies.

RESULT AND DISCUSSION

An upstream oil and gas corporation based in Java manages 90 different types of MRO inventories in its warehouse. The company shows that just 33% of goods were managed optimally, implying that user demand was met without shortages or surplus inventory. However, shortages remain the most pressing issue, affecting 36 goods (40% of total inventory). This happens when available quantities fall short of requirements, resulting in unfulfilled operational needs and the possibility of downtime that could interrupt production [36] Overstock situations were discovered in 24 goods (27%), resulting from receipts without issues, which left materials idle in the warehouse. Such accumulation enhances the risk of obsolescence while also increasing storage and maintenance costs [6]. Overall, shortages in 36 items directly threaten operational continuity, as MRO unavailability has been consistently linked to delayed maintenance actions, prolonged equipment downtime, and elevated operational costs in capital-intensive industries, including oil and gas [37]. Meanwhile, overstock in 24 items contributes to elevated holding costs, which typically represent 20-30% of total inventory value annually, encompassing warehousing, handling, insurance, and obsolescence risks [38], [39]. Together, these conditions underscore the urgency of improving MRO inventory management practices to safeguard operational continuity and cost efficiency.

The ABC classification

Table presents the MRO classification into three categories based on their value contribution. The study's results indicate that the classification identified five MRO materials belonging to Class A, representing approximately 6% of the total MRO items. Furthermore, twelve MRO materials were classified into Class B, while the remaining seventy-three materials were categorized as Class C. A summary of the ABC classification is presented in Figure 2

The significant cost concentration revealed in class A, where just 6% of total SKUs absorb 80% of total spending, is due to structural issues inherent in the upstream oil and gas business. MRO in this sector is primarily associated with critical production equipment such as rotating machinery, pressure vessels, and subsurface tools, whose spare parts have high unit costs and engineering-grade specifications; their unavailability directly causes unplanned production downtime, driving expenditure concentration toward a small subset of critical items [40]. This cost pressure is exacerbated by the remote and offshore character of upstream activities, which limits supplier availability, lengthens lead times, and reduces price negotiating power – circumstances that systematically increase unit acquisition prices [40]. Furthermore, the lack of a structured inventory management framework before ABC implementation tends to perpetuate suboptimal ordering behaviors, such as excessive safety stock accumulation and recurrent emergency procurement at a premium price [41], resulting in increased cost concentration among the most critical items.

In terms of cost contribution, these findings are consistent with a body of previous research. For example, a case study in Indonesia's Aviation MRO found that a small proportion of items (Class A) accounted for a large share of 70% or more of total inventory [20]. Similarly, the gearbox manufacturing industry, a recent study applying a multi-criteria ABC classification demonstrated that although only a few items fall into Class A, these items dominate cost, reinforcing the structural pattern observed in the present study.

Table 3. The result of the ABC classification

MRO MATERIAL	UNIT PRICE (IDR)	NUMBER OF DEMAND	TOTAL VALUE (IDR)	% VALUE	VALUE CUMULATIVE	CLASS
TUBING, 2.7/8 IN, J-55, EU, R2, 6.50 PPF	5,277,104	1,809	9,546,281,136	25.757%	25.757%	A
….	….	….	….	….	….	…
LINER HANGER,7 IN-23 X 9-5/8IN - 36 PPF	975,000,000	3	2,925,000,000	7.892%	74.421%	A
LINER HANGER,9.5/8X7,	1,125,000,000	2	2,250,000,000	6.071%	80.492%	B

MRO MATERIAL	UNIT PRICE (IDR)	NUMBER OF DEMAND	TOTAL VALUE (IDR)	% VALUE	VALUE CUMULATIVE	CLASS
MECH, L80, TSH BLUE						
….	….	….	….	….	….	
SUCKER ROD, SIZE 7/8 IN, 25 FT, D	1,506,176	520	783,211,520	2.113%	87.743%	B
…..	…..	…..	…..	…..	…..	…..
PCKR, MSG,658,17-20,300F,5K, L80,278EU	82,800,000	2	165,600,000	0.447%	95.015%	C
ELECTRODE, ROD EW, ADV.ALLOY	1,472,500	100	147,250,000	0.397%	95.413%	C
PIPE, CS, 5L, B, SMLS, BE, DRL, 2IN, SCH80	1.824.071	67	122,212,757	0.330%	95.742%	C
…..	…..	…..	…..	…..	…..	…..
STUFFING BOX,1.1/4 X 3 IN, TRICO	535,054	1	535,054	0.001%	100%	C

The VED classification

The VED classification was carried out utilizing the criticality matrix in Table and the structured interview technique. **Figure 1** depicts the classification matrix used to assign materials to criticality groups. Table shows the resulting classification. Of the 90 items, 47 (52%) were rated as Vital, 17 (19%) as Essential, and 26 (29%) as Desirable, as presented in Figure 3.

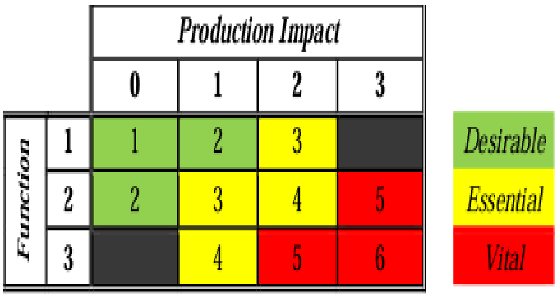

Figure 1. The critical assessment matrix

The high amount of Vital elements (52%) is significant and requires contextual interpretation. In hospital VED research, Vital items typically account for 20-35% of total inventory [7], [21]. The elevated Vital proportion in this study reflects the operational characteristics of upstream oil and gas production. The majority of MRO materials are directly associated with wellbore integrity (tubing, packers, hangers), artificial lift systems (sucker rods, pumping units), and pressure control equipment – functions whose failure results in an immediate well shutdown. This conclusion is consistent with research in an Indonesian oil field that found a comparable high proportion of crucial spare parts [11] and research that proved that emergency spare part requirements in power plants are driven by a small number of irreplaceable components [42]. The consequence is that the upstream oil and gas sector has a larger criticality risk than sectors investigated in previous VED studies, emphasizing the importance of a specialized inventory system

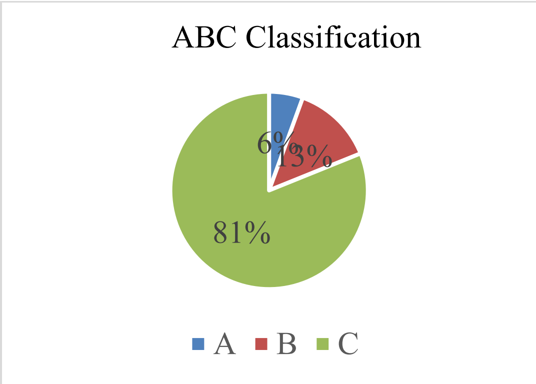

Figure 2. The ABC classification

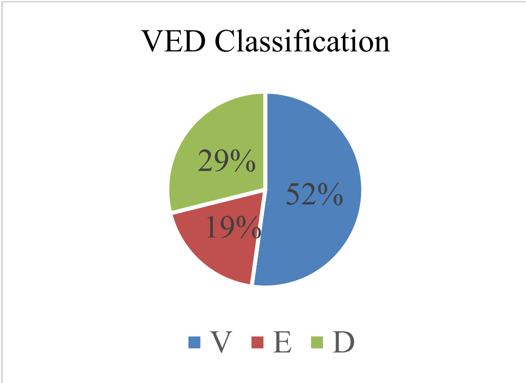

Figure 3. The VED classification

Table 4. The result of the VED classification

NO	MRO MATERIAL	CATEGORY
1	BOLT, STUD,2N, A193B7,1.1/2IN-8UNC X 9 IN	Vital (V)
….	…..	…..
47	XN NOGO LANDING NIPPLE, 2.7/8", L80, EU	Vital (V)
48	CLAMPS, PIPE REPAIR,6IN,220MM,5.255SA	Essential (E)
….	…..	…..
64	X-OVER, TBG,2.7/8"EUE PIN X 3.1/2"EUE BOX	Essential (E)
65	BABBIT, METAL, ALLOY ASTM B236R3	Desirable (D)
…	…..	…..
90	WIRE ROPE,6X37, IWRC,9/16 IN, RHOL	Desirable (D)

The ABC – VED matrix

The ABC-VED matrix combines the cost and criticality elements into a unified classification. There were no items in the AE or AD subclasses in the current dataset. Category I, as shown in **Figure 4**, includes items from the AV (5 items), BV (7 items), and CV (35 items) subclasses, for a total of 47 (52%). Category II has 22 items (25% from the BE, BD, and CE subclasses, whereas Category III contains 21 items (23%) from the CD subclass. Table shows items from Category I. The ABC-VED matrix analysis also indicates that 22 types of MRO materials fall into Category II and 21 types fall into Category III, as shown in **Table**

The concentration of 52% of MROs in Category I, which bear both high operational criticality and diverse levels of cost, has significant managerial implications. Most importantly, the matrix exposes a structural conflict between cost and criticality: 35 of the 47 Category I MROs are in the CV subclass, which means they are inexpensive (Class C), but operationally critical. A pure ABC method would identify these items as low-priority, systematically diverting management efforts away from components whose absence would result in a rapid production shutdown. This conclusion gives a strong empirical demonstration of why single – method classification is insufficient in the upstream oil and gas sector, and why an integrated approach is required. The ABC-VED matrix provides an analytical foundation for the three management categories' distinct control policies. Category I should be managed using strict, continuous-review rules, including dedicated safety stock and preferred supplier agreements. Category II requires periodic review systems with moderate safety stock, balancing availability and holding costs. Category III can be controlled using simplified procedures such as bulk purchase, reduced monitoring frequency, and decentralized storage to reduce administrative overhead.

Table 5. The MRO material under category I

NO	MRO MATERIAL	ABC CLASS	VED CATEGORY
1	TUBING, 2.7/8 IN, J-55, EU, R2, 6.50 PPF	A	V
2	TUBING, 3.1/2 IN, N-80, 9.3 PPF, EUE, R2	A	V
…	…..	…..	…..
6	LINER HANGER,9.5/8X7, MECH, L80, TSH BLUE	B	V
7	TUBING, 3.1/2 IN, L-80, 9.3 PPF, EUE, R2	B	V
…	…..	…..	…..
14	PCKR, MSG,658,17-20,300F,5K, L80,278EU	C	V
15	PIPE, CS,5L, B, SMLS, BE, DRL,2IN, SCH80	C	V
…	…..	…..	…..
47	BOLT, STUD, A193, B7,1/2IN,3.1/2IN,2NUT	C	V

These findings are aligned with prior research that emphasizes the importance of categorizing spare parts based on operational criticality. For instance, the VED framework is particularly useful in ensuring the availability of critical components that directly influence production continuity and system reliability [43]. Moreover, another study has highlighted that identifying Vital items provides an effective framework for resource prioritization, as these items are often linked to high downtime risk when unavailable [44]. Taken together, these studies reinforce the value of the present research in showing that more than half of the MRO items analysed fall into the Vital category, underscoring the significant operational risks associated with their unavailability.

Table 6. The MRO material under categories II and III

CATEGORY II				CATEGORY III			
No	**MRO Material**	**ABC Class**	**VED Category**	**No**	**MRO Material**	**ABC Class**	**VED Category**
1	SODIUM CHLORIDE, NACL,50 KG/BAG	B	E	1	CROSS, 3 IN	C	D
2	TUNGSTEN CARBIDE ROD, SIZE: 5/16x1/4 IN	B	D	2	ELECTRODES, WELDING, AWS E-7016,3.25MM	C	D
…	…..	…..	…..	…	…..	…..	…..
7	X-OVER, TBG,2.7/8"EUE BOX X 3.1/2"EUE PIN	C	E	21	FLAP, 10.00 IN, 20 IN	C	D
8	OIL WELL CEMENT CLASS G API SPEC 10A	C	E				
…	…..	…..	…..				
22	STUFFING BOX,1.1/4 X 3 IN, TRICO	C	E				

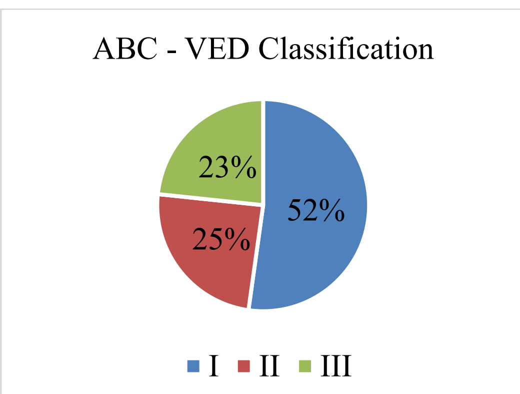

Figure 4. The ABC-VED classification

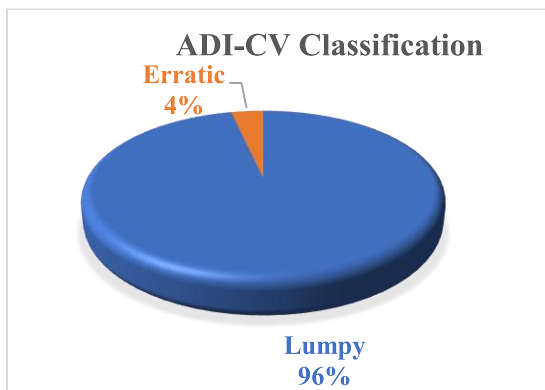

Figure 5. The ADI-CV classification

The ADI – CV classification

Table . Once the material usage data were obtained, the subsequent step involved calculating the ADI and CV

For the ADI-CV analysis, demand data for 90 MRO material types throughout 2024 were collected, as presented in values. The ADI was determined using (1), whereas the CV was calculated using (2).

Table 7. The MRO materials demand data

NO	MRO MATERIAL	MONTHLY DEMAND				TOTAL	BASE UNIT OF MEASURE
		1	2	…..	12		
1	BABBIT, METAL, ALLOY ASTM B236R3	0	50	…..	20	70	KG
2	BOLT, STUD, 2NA193B7,1.1/2IN-8UNC X 9 IN	0	0	…..	72	72	PCS
3	BOLT, STUD, A193, B7,1.1/8IN,215MM, UNC, HEX	0	0	…..	32	88	PCS
4	BOLT, STUD, A193, B7,1.3/8IN,295MM,2NUT	0	0	…..	92	128	PCS
…	…..	…..	…..	…..	…..	…..	…..
90	X- OVER, TBG,2.7/8"EUE PIN X 3.1/2"EUE BOX	0	0	…..	3	3	JT

The results of the ADI-CV analysis are summarized in Table . The ADI-CV classification results reveal that 86 material types display a lumpy demand pattern, whereas 4 material types exhibit an erratic demand pattern, as shown in **Figure 5**.

Table 8. The results of ADI – CV classification

NO	MRO MATERIAL	Ti	N	ADI	CV	DEMAND PATTERN
1	BABBIT, METAL, ALLOY ASTM B236R3	10	2	5	5.97	Lumpy
2	BOLT, STUD, 2NA193B7,1.1/2IN-8UNC X 9 IN	11	1	11	8.12	Lumpy
3	BOLT, STUD, A193, B7,1.1/8IN,215MM, UNC, HEX	9	3	3	4.86	Lumpy
4	BOLT, STUD, A193, B7,1.3/8IN,295MM,2NUT	10	2	5	8.10	Lumpy
…	…..	…..	…..	…..	…..	…..
70	SUCKER ROD, SIZE 3/4 IN, 25 FT, D	3	9	0.33	6.48	Erratic
…	…..	…..	…..	….	…..	…..
90	X- OVER, TBG,2.7/8"EUE PIN X 3.1/2"EUE BOX	11	1	11	1.66	Lumpy

The ADI values for the 90 MROs ranged from 0.33 to 11.00, whereas CV values ranged from 0.91 to 52.44. The mean ADI was 6.95 with the standard deviation at 3.74, and the mean CV was 7.80 with the standard deviation at 7.90, showing that the typical MRO item is needed less than twice per year and has demand quantity variability above the 0.49 threshold. The near-universal prevalence of Lumpy demand (96%) is consistent with findings from previous ADI-CV studies in spare parts management [18], [22], [33] and aligns with the project-driven and maintenance-triggered consumption patterns characteristic of upstream oil and gas operations, where materials are consumed in sporadic bursts tied to well interventions, scheduled maintenance outages, or unplanned equipment failures. The complete absence of Smooth or Intermittent items (demand patterns for which normal forecasting methods are acceptable) suggests that all 90 MRO items necessitate specific intermittent demand forecasting methods. The Syntetos-Boylan Approximation (SBA) or bootstrapping procedures [18], [23] are most suited for the 86 lumpy items, as they have been empirically proven to beat Croston's original method under lumpy conditions [33]. In addition, inventory policies must be tailored to address the high uncertainty associated with lumpy demand, which may involve setting higher safety stock levels, adopting more frequent review cycles, or collaborating closely with suppliers to ensure responsiveness. The four Erratic items, defined by relatively frequent but highly variable demand, necessitate differentiated strategies, such as contingency supplier agreements and flexible minimum order quantities, as standard safety stock calculations based on normal demand assumptions will consistently underestimate the required buffer [45].

The Integrated MRO Classification Method

Highly critical MRO materials are identified through the integration of ABC, VED, and ADI-CV analyses, providing a comprehensive assessment of value, operational importance, and demand variability. ABC analysis prioritizes high-cost items, VED classifies materials based on operational criticality, and ADI-CV identifies items with lumpy or erratic demand patterns. In this study, the highly critical MRO materials are those classified within the AV subclass and exhibiting a lumpy demand pattern. These materials require stringent inventory control to prevent stockouts and ensure uninterrupted production. Detailed information on these materials, based on the integrated classification, is presented in Table .

Table 9. The highly critical MRO materials

NO	MRO MATERIAL	ABC CLASS	VED CATEGORY	DEMAND PATTERN	CONCLUSION
1	TUBING, 3.1/2 IN, N-80, 9.3 PPF, EUE, R2	A	Vital	Lumpy	Highly Critical
2	TUBING, 2.7/8 IN, N-80, 6.5 PPF, EUE, R2	A	Vital	Lumpy	Highly Critical
3	TUBING, 2.7/8 IN, L-80, 6.5 PPF, EUE, R2	A	Vital	Lumpy	Highly Critical

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The classification of these three tubing items as highly important has significant operational implications. Tubing strings are the primary conduit through which hydrocarbons are lifted from the reservoir to the surface and are thus critical to production continuity. Their unavailability does more than only reduce output; it entails a well shutdown, with rehabilitation necessitating the mobilization of workover personnel and equipment, which can take days to weeks to organize, depending on the availability of field resources. All three items are classified as Class A; their acquisition already accounts for a disproportionate part of inventory spending. A stockout of any of these items would thus result in both operational losses (production shutdown) and capital pressure (expensive emergency purchase at premium pricing). Their lumpy demand profile – with ADI values of 7-11 months and CV values well exceeding 1.0 means that standard safety stock formulae (which assume normally distributed demand) will consistently and significantly underestimate the required buffer. This triple convergence of financial exposure, operational necessity, and projection difficulties distinguishes these three items as especially high-priority in the company's MRO portfolio.

The relationship between these three inventory strategies can be understood by considering what each method would create if applied independently. Using ABC analysis alone, the five Class A items would be appropriately identified as high-cost priorities. Still, they would be treated similarly, regardless of how critical each item is to operations. Using VED analysis alone, all 47 Vital items would be considered equally significant, providing no evident reason to choose the three AV items above the remaining 42 BV and CV items. Meanwhile, the ADI-CV analysis alone would only provide an understanding of the demand patterns for all 90 items, not the level of financial or operational risk associated. This is precisely why all three strategies must be utilized simultaneously. By combining them, it can accurately identify three items – out of 90 – that really require the highest priority attention: items where mismanagement would cause the most harm, and items where proper management would provide the most significant operational and financial benefit to the company.

CONCLUSION

This study developed and empirically tested an integrated three-dimensional MRO inventory classification framework – combining ABC, VED, and ADI-CV analyses – applied to 90 MRO items at an upstream oil and gas company in Java, Indonesia. Three key findings emerged: ABC analysis revealed significant cost concentration, with just 6% of items accounting for approximately 80% of total inventory cost, driven by high-unit-cost downhole tubulars and wellbore equipment; VED analysis classified 52% of items as Vital, reflecting the prevalence of production-critical equipment whose failure triggers immediate well shutdown; and ADI-CV analysis found that 96% of MROs exhibit lumpy demand patterns, confirming that virtually the entire portfolio requires an intermittent-demand forecasting method and that standard forecasting approaches are inappropriate for this inventory. The integrated framework's practical advantage over any single-method approach is quantified by the residual risk that each method leaves unaddressed when used alone. When the ABC analysis is applied independently to the 90 MRO items, only 5 Class A items (6%) are identified as high-priority, while the remaining 85 items are classified as moderate or low-priority, leaving 42 operationally Vital items (47%) unseen in the priority hierarchy. VED analysis alone would highlight all 47 Vital goods identically, leaving no way to distinguish the 5 Class A items that account for 80% of inventory cost from the 42 lower-priced Vital items. ADI-CV analysis alone would disclose that 96% of items have lumpy or unpredictable demand, but there is no way to assess their financial or operational relevance. Only by simultaneous integration are three items discovered – accounting for only 3.3% of the overall portfolio – as the convergence point of all three risk dimensions. These items represent the convergence of the three highest-risk dimensions, including large financial exposure, operational indispensability, and severe demand uncertainty, and thus warrant dedicated management attention, such as continuous review of inventory policies, SBA or Croston-based demand forecasting with safety stock calibrated for lumpy demand, blanket purchase orders or preferred supplier agreements to reduce procurement lead-time uncertainty, and direct oversight by an inventory manager. This study contributes new insights to the inventory management literature. Theoretically, it demonstrates that the three classification dimensions — ABC, VED, and ADI-CV — are synergistic rather than additive; their simultaneous integration reveals structural inventory tensions, particularly the coexistence of stockout and overstock risk, that no single-method or dual-method approach can identify. Most importantly, the practical consequences for management are significant. The integrated framework provides inventory managers with a reproducible, systematic tool for MRO prioritization that directly informs critical managerial decisions, such as setting differentiated safety stock levels based on combined priority class, determining review frequency proportional to operational criticality, selecting and managing suppliers according to item vitality and demand unpredictability, and allocating procurement budgets toward items whose stockout consequences. This study contains some limitations that should be considered in future research. First, the VED assessment, while organized and cross-validated, is based on expert opinion from a single informant. Future research should employ multi-rater procedures with rigorous inter-rater reliability assessments, such as Cohen's kappa, to quantify and decrease subjective bias. Second, this study is limited to the classification of MRO materials and does not extend to quantifying the economic impact of the proposed framework. Efficiency gains — such as reductions in inventory costs, improvements in service levels, and safety stock optimization — remain unquantified, as measuring these outcomes falls beyond the scope of this research. Future studies should address this gap by applying a continuous review method combined with Syntetos-Boylan Approximation (SBA) forecasting to the identified critical MRO materials. This combination is particularly appropriate given the erratic and lumpy demand patterns characteristic of MRO items, and will enable subsequent researchers to empirically calculate forecast error reductions, determine optimal reorder points and order quantities, and quantify the cost savings attributable to the classification framework established in this study.

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