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A System-Based Classification and Prioritization Model to Prevent Dead Stock Occurrence in Retail Store Systems

Richard LI[a,1], Rosemary SEVA[a], and Anthony CHIU[a]
[a] *De La Salle University*
ORCiD ID: Richard Li https://orcid.org/0000-0001-6039-6180
Rosemary Seva https://orcid.org/0000-0002-6971-3012
Anthony Chiu https://orcid.org/0000-0003-2411-7302

Abstract. Retail chain stores commonly experience dead stock inventory accumulation due to the absence of indicators and decision rules in the inventory management system to track down the impact of potential dead stocks when left "unattended" or "unmanaged" in the warehouse. Potential dead stocks are inventory items that are either near-expiry, near its end-of-season, near the end of its product market life cycle, or simply slow moving which will soon become dead stocks in the warehouse if not managed in a timely manner. Most retail systems have focused on fighting the dead stock fire rather than developing a standardized process to manage inventories and prevent potential dead stocks from becoming dead stocks. The systematic management perspective is to identify the potential dead stocks first and then apply the best strategies to prevent the occurrence of dead stocks. This research aims to develop a standardized potential dead stock identification and prioritization framework that will provide the level of priority for management intervention using decision rules. Literature review is performed to develop the indicators required. The framework is then validated through hypothetical data sets. As a result, the classification phase shows that the data sets produced similar industry findings on dead stock composition as a percentage of total inventory. Next, the prioritization phase shows that considering a 10-4-1 risk weight produces more discriminating ranks than a 9-3-1, adopted from the House of Quality (HOQ) framework. The rank discrimination is an important metric for this to address the primary research objective as it represents the ability of the framework to prioritize intervention given urgency based on criteria and resource constraints. Further research may be performed on enhancing the decision rules used in producing the prioritization output of the developed framework.

Keywords. retail chain stores, inventory management system, inventory management indicators, potential dead stocks, standardized classification and prioritization

1. Introduction

Across all levels of the supply chain, specifically in the retail chain store level, there is a common issue on the accumulation of dead stocks, which is considered as an obsolete product or raw material [1]. Normally, inventory products are categorized into fast, slow,

[1] Corresponding Author: Richard Li

and non-moving based on market demand [2]. Product characteristics and the industry to which a product belongs influence market dynamics as well as the rate at which a product experiences growth, maturity, and decline. The market forces that act upon these products impact the inventory movement, inventory level, and ultimately the products' market life cycle.

The slowdown in inventory movement and the increase in a product's inventory level are primary indicators of a potential dead stock [3][6]. When these indicators are ignored, potential dead stocks accumulate over time and become dead stocks especially if products are vulnerable to obsolescence [4]. Product expiration [7], seasonality [2], technological and functional obsolescence [1] quickly turn these potential dead stocks into dead stocks. As such, potential dead stocks must be systematically identified and managed in a standardized manner to prevent these inventories from becoming a non-moving inventory or dead stock [3].

The transition in inventory movement from slow-moving to non-moving status occurs when there is a continued slowing down of products being sold. The absence of monitoring measures that can trigger timely management of these products at the slow-moving level leads to overstocking and consequently, excessive inventory levels [5]. This situation therefore necessitates the identification and recognition of these slow-moving stocks as potential dead stocks as well as the immediate management of these products at that level of inventory movement [6].

The retail industry is characterized by high volume products that are heavily dependent on end-user demand to sustain inventory movement. This reliance on a very dynamic, sensitive, and competitive end-user demand exposes retailers to high risks of products turning from fast to slow-moving inventories [3] until eventually becoming dead stocks in the warehouse. Not recognizing the maturity and decline stages in a product's market cycle in a timely manner produces serious implications on sales and inventory levels, particularly in retail chain stores such as supermarkets and fast fashion outlets where there are hundreds or even thousands of different products being sold [7].

Past studies have developed management-based and strategy-based proactive and reactive solutions in solving the dead stock problem [3]. However, these solutions focused only on the non-moving inventories or dead stocks. The critical process of identifying and prioritizing the management of these potential dead stocks in the inventory system has largely been ignored as an important first step in preventing the occurrence of the dead stock problem. As such, creating a standardized process of recognizing slow moving inventories (also known as potential dead stocks) and prioritizing efforts to market these products improve sales and reduce the possibility of these potential dead stocks turning into dead stocks [3]. Once these potential dead stocks have been identified, different strategies may be applied to push these products out of the chain stores, thereby preventing the accumulation of dead stocks in the retail shelves and warehouses. The primary objective of the study is to address the issue of late detection of dead stocks through a standardized system of routine identification and prioritization of potential dead stocks in the inventory system.

2. Literature Review

In the retail industry, products are usually in high-volume levels [7], where the inventory movement depends on the demand levels [3]. When the inventory movement slows down, there is a high risk of the products becoming obsolete or accumulate as dead stocks [4]. Dead stocks may be either proactively or reactively managed. Proactive strategies are commonly composed of forecasting and big data and analytics methods and tools to accurately measure the stock levels and order points [1][3]. Reactive strategies utilize different measures to efficiently respond to the accumulation of dead stocks, where commonly used methods are lateral transshipment, product bundling, disposal, and burning [3].

Both tracks of dead stock management are helpful in addressing the dead stock accumulation problem but have not explored the idea of a system-based approach that detects the transition of inventory movement to a slow-moving and ultimately to a non-moving state. If management intervention is not performed through proactive or reactive strategies at a point when inventory is already moving slowly, inventory builds up without being noticed until warehouses are filled with the unwanted dead or non-moving inventories. Handling the dead stocks after they have accumulated may be too late, having incurred holding costs and the risk of obsolescence [4]. These strategies are not adequate in preventing the occurrence of dead stocks. The idea is to prevent the occurrence and not the accumulation. This may be performed through a system-based inventory classification and categorization approach that would identify the categories of inventory movement in a standardized and timely manner. The classification and categorization of inventory is done to ultimately identify the presence of slow-moving inventories. Slow-moving inventories are defined as inventories that travel, sell, and replenish slower than other inventories [2][5]. These slow-moving inventories are known as potential dead stocks, and if they are not recognized in a timely manner, they may transform into dead stocks due to accumulation over time [3].

To perform the classification of inventory, there must be a monitoring of key indicators that warn retailers about the presence of potential dead stocks in the inventory system. The indicators include product expiration [3][7], inventory movement [2], and inventory level [8]. The monitoring of product expiration and timely action on products that have short actual remaining shelf life allow retail businesses to prevent dead stocks in the warehouse that occur in the form of spoiled products [7]. Inventory movement must also be measured and monitored to determine the state of the inventory items based on demand levels and to alert management once there is a shift from slow-moving to non-moving inventories [4]. Slow-moving inventories are identified based on the speed of their movement out of the warehouse or the duration of their stay in the warehouse. This often-ignored inventory transition from a slow-moving to a non-moving state result in the accumulation of dead stocks that cause problems in warehouse space and inventory cost management [3]. Lastly, the inventory level is related to the inventory movement metric, as it represents the level of products in stock in a specific period. A study was able to develop a method in determining inventory movement through the application of ABC Analysis and Min-max Analysis on the inventory levels to classify the items and determine the inventory limits [5]. However, it only seeks to classify inventories rather than determine the level of intervention priority of the inventories.

The classification of inventory leading to the identification of potential dead stocks is just the first step in the prevention of dead stock occurrence. Given the large volume of potential dead stocks in retail store systems, management should be guided in selecting the potential dead stocks that require the most urgent attention for management intervention. This may be done through a priority rating procedure based on a set of decision rules [3] or by modifying the ABC Analysis [5]. The prioritization phase is to be performed after the inventory classification phase to objectively rank the potential dead stocks for strategy intervention.

A method to prioritize the potential dead stocks is through the consideration of risk factors, where risk is defined as a potential fluctuation from the initial objective of a system [10]. Risk factors are computed in retail industry operations to consider uncertainty and potential impacts of a decision made in the system [10]. To calculate risk, it commonly considers the components of potential inventory costs as cost savings [2], include product acquisition cost, profit margin, and warehouse or holding cost [2][3][5]. The inventory cost components are considered as an operational key performance indicator for inventory. In relation to the inventory costs, profit margin is considered as a risk component as it represents the sales performance indicator for inventory [2].

Through inventory classification and prioritization of potential dead stocks in retail industries, a standardized process is developed that focuses on the prevention of dead stock occurrence at the point of sustained slow movement of inventories. The different monitoring measures and factors for prioritization allow inventories to be objectively assessed and ranked for management intervention.

3. Methodology

The research methodology includes an extensive literature review on the concept of potential dead stocks and how they are currently identified and managed within retail store systems. Limitations of existing dead stock management processes and solutions were addressed through the standardized process of identifying and managing potential dead stocks developed in this research. A proposed potential dead stock classification and prioritization framework is developed and shown in Figure 1.

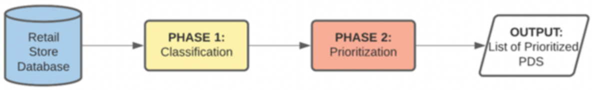

Figure 1. Proposed Potential Dead Stock Classification and Prioritization Framework.

The proposed framework has two (2) phases, namely the classification and prioritization phases. The inputs are sourced from the retail store database or Enterprise Resource Planning (ERP) system, while its final output will be the list of prioritized potential dead stock (PDS). Figure 2 shows the specific inputs, process, and outputs for the classification phase. This implies that retail stores must acquire their data inputs from their ERP system as these are expected to be available or can be made available through their database. Standardizing the classification phase using the regular inputs from the ERP system would help generate a real-time report for inventory classified as PDS on a periodic basis.

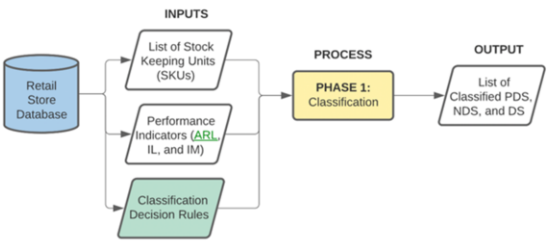

Figure 2. Phase 1: Potential Dead Stock Classification Framework.

The classification phase identified the potential dead stock items using inventory management performance indicators that include Actual Remaining Shelf Life (ARL), Inventory Movement (IM), and Inventory Level (IL). The metrics classify if the inventory is a Dead Stock (DS), Potential Dead Stock (PDS), or Not a Dead Stock (NDS). Table 1 shows the definitions, computations or data sources, and indicator classification.

Table 1. Phase 1: Potential Dead Stock Classification Definitions and Rules

Performance Indicator	Definition	Data Source / Computation	Decision Rules for Classification
Actual Remaining Life (ARL)	The actual number of days left before the product expiration date, measured against the retailer policy on maximum number of days before expiration with lower bound, a and upper bound, b.	ARL (in days) = Expiry Date – Current Date *Inputs are taken from the retail store database	• If ARL ≥ b, then Far from Expiry / NDS; • If a ≤ ARL < b, then Near Expiry / PDS; and • If ARL < a, then Expired / DS
Inventory Movement (IM)	The actual rate of product movement based on its turnover ratio, measured against the retailer policy on maximum number of days before expiration with lower bound, c and upper bound, d.	Turnover Ratio (TR) = $\frac{\textit{Annual Demand (in units)}}{\textit{Average Inventory (in units)}}$ *Inputs are taken from the retail store database	• If TR > d, then Fast Moving / NDS; • If c < TR ≤ d, then Slow Moving / PDS; and • If TR ≤ c, then Non-moving / DS
Inventory Level (IL)	The actual maintaining inventory level of the product, measured against the retailer maintaining inventory level interval policy maintaining inventory level with lower bound, e and upper bound, f.	Taken from the retail store database	• If IL < e, then Low / NDS; • If e ≤ IL ≤ f, then Moderate / PDS; and • If IL > f, then High / DS = IL - f

The ARL screening considers the expiration date of the product and is identified as a valuable performance indicator since the expiration of a product must be monitored regularly by retail stores. This implies that the ARL values may vary daily since this is regularly monitored by the system. In addition, the IM screening involves the use of FSN Analysis from a study [5] to help classify the items using computations of turnover ratio, where it follows a classification ruling system. The IM reflects the demand of the item, as the turnover ratio is triggered primarily by demand to its existing inventory. Lastly, the IL screening indicates the presence of unwanted or excess stocks in the inventory system. It reflects the performance of the ordering or inventory policy of the retail store. The ARL and IL screening also follow a set of retailer decision rules based on inventory management threshold.

Table 2 shows the final classification for the different combinations of DS, PDS, and NDS, which consists of 27 permutations.

Table 2. Phase 1 Final Classification

CLASSIFIED IM	CLASSIFIED ARL	CLASSIFIED IL	FINAL CLASSIFICATION	JUSTIFICATION
NDS	NDS	DS	NDS	Fast Moving and Far from Expiry items can compensate for Moderate IL.
NDS	NDS	PDS	NDS	Fast Moving and Far from Expiry items can compensate for Moderate IL.
NDS	NDS	NDS	NDS	All are NDS.
NDS	PDS	DS	PDS	Although Fast Moving, it has High IL and is Near Expiry.
NDS	PDS	PDS	NDS	Fast Moving and Near Expiry items can compensate for Moderate IL.
NDS	PDS	NDS	NDS	Fast Moving and Near Expiry items can compensate for Low IL.
NDS	DS	DS	DS	It is expired.
NDS	DS	PDS	DS	It is expired.
NDS	DS	NDS	DS	It is expired.
PDS	NDS	DS	PDS	The combination might yield to excess stocks.
PDS	NDS	PDS	PDS	The combination might yield to excess stocks.
PDS	NDS	NDS	NDS	Slow Moving and Far from Expiry items have higher chances of clearing out the stocks before expiry.
PDS	PDS	DS	PDS	The combination might yield to excess stocks.
PDS	PDS	PDS	PDS	All are PDS.
PDS	PDS	NDS	PDS	The combination might yield to excess stocks.
PDS	DS	DS	DS	It is expired.
PDS	DS	PDS	DS	It is expired.
PDS	DS	NDS	DS	It is expired.
DS	NDS	DS	PDS	Non Moving already; stocks will remain since there is no stock movement.
DS	NDS	PDS	PDS	Non Moving already; stocks will remain since there is no stock movement.
DS	NDS	NDS	PDS	Non Moving already; stocks will remain since there is no stock movement.
DS	PDS	DS	DS	Non Moving already; stocks will remain since there is no stock movement.
DS	PDS	PDS	DS	Non Moving already; stocks will remain since there is no stock movement.
DS	PDS	NDS	DS	Non Moving already; stocks will remain since there is no stock movement.
DS	DS	DS	DS	All are DS and it is expired.
DS	DS	PDS	DS	It is expired.
DS	DS	NDS	DS	It is expired.

Each combination was scrutinized based on the combined (net) effect of the three performance indicators to come up with logically defined rules for an inventory's final classification. It follows these general rules for the final classification:

1. If ARL is Expired / DS, then the final classification is DS, since an expired product may not be sold.
2. If IM is Fast Moving / NDS and ARL is Far from Expiry / NDS, then the final classification is NDS, regardless of the IL. This is due to the high probability of the product being sold within the timeframe before expiration, resulting in minimal chances of becoming a potential dead stock or a dead stock.

Figure 3 shows the PDS prioritization phase. Similarly, the prioritization phase will use the ERP system to gather relevant inputs but will additionally utilize the output of the classification phase, which is the list of inventories classified as PDS. This phase generates a ranked list of items for management intervention.

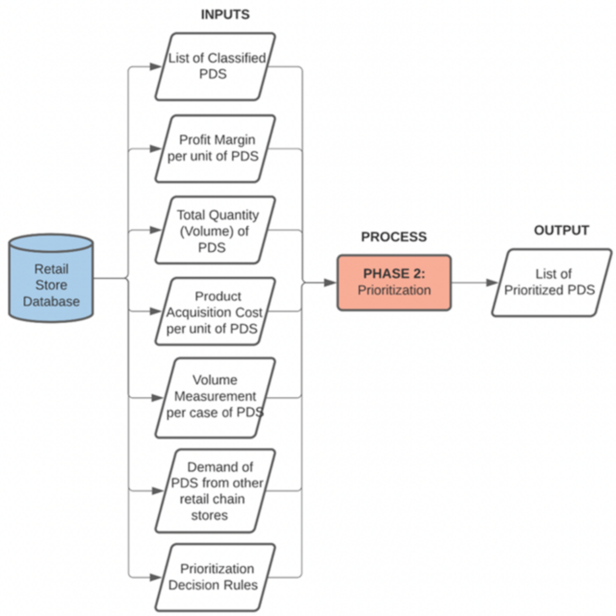

Figure 3. Phase 2: Potential Dead Stock Prioritization Framework.

The prioritization phase utilizes the concept of risk to rank the classified PDS items (from the classification phase) for management intervention based on the risk factors of product acquisition cost, profit margin, and used storage space, which were determined through the literature review. The prioritization phase computations are based on the ABC Analysis method [5] to rank the PDS items. However, there are modifications made for the prioritization phase of the framework. The modified ABC Analysis tool will compute for the product space consumption based on quantity of PDS items. In this method, product space value will be based on packaging size dimensions of the SKUs. Therefore, the identified risk factors for the prioritization phase are Product Cost-Volume (PCV), Profit Margin-Volume (PMV), Product Space-Volume (PSV), Product Demand from Other Stores (PDO), and PDS and DS Indicator (PDSI) respectively. In addition, an added risk indicator of the number of PDS and DS present in the classification phase is considered relevant in the prioritization phase. This is referred to as the PDS and DS Indicator (PDSI). The definitions, computations or data sources, and risk classification (i.e. Low, Medium, High) are defined, as shown in Table 3.

Table 3. Phase 2: Potential Dead Stock Prioritization Definitions and Rules

RISK FACTOR	DEFINITION	DATA SOURCE / COMPUTATION	RISK CLASSIFICATION
Product Cost-Volume (PCV)	The actual total product acquisition cost with reference to the PDS volume (in number of units), measured against the retailer PCV interval policy with upper bound of PCV, b and lower bound of PCV, a.	PCV (in currency units) = Product Acquisition Cost x Quantity of PDS Items *Inputs are taken from the retail store database, while Quantity of PDS Items is taken from Phase 1.	• If PCV < a, then Low; • If a ≤ PCV < b, then Medium; and • If PCV ≥ b, then High
Profit Margin-Volume (PMV)	The actual total profit margin with reference to the PDS volume (in number of units), measured against the retailer PMV interval policy with upper bound of PMV, d and lower bound of PMV, c.	PMV (in currency units) = Profit Margin x Quantity of PDS Items *Inputs are taken from the retail store database, while Quantity of PDS Items is taken from Phase 1.	• If PMV < c, then Low; • If c ≤ PMV < d, then Medium; and • If PMV ≥ d, then High
Product Space-Volume (PSV)	The actual total product space used with reference to the PDS volume (in number of units), measured against the retailer PSV interval policy with upper bound of PSV, f and lower bound of PSV, e.	PSV (in cubic units) = Product Case Volume x Quantity of PDS Items *Inputs are taken from the retail store database, while Quantity of PDS Items is taken from Phase 1.	• If PSV < e, then Low; • If e ≤ PSV < f, then Medium; and • If PSV ≥ f, then High
Product Demand from Other Store (PDO)	The demand level from other retail store branches, which is measured through the retailer interval policy for PDO with lower bound, g and upper bound, h.	*Product Demand from Other Store is taken from the retail store database.	• If PDO < g, then Low; • If g ≤ PDO < h, then Medium; and • If PDO ≥ h then High
PDS and DS Indicator (PDSI)	The number of PDS and DS indicators present in the classification phase for all the performance indicators (i.e. ARL, IM, and IL).	*Number of PDS and DS is taken from the Classification Phase.	• If 0 ≤ PDS ≤ 1 and DS = 0, then Low; • If 2 ≤ PDS ≤ 3 and DS = 0, then Medium; and • If DS ≥ 1, then High

With the risk classification per PDS item, a scoring system is performed per SKU to determine its total risk rating score. A risk-weighted scoring system is used to properly discriminate the ranking of PDS items based on the weights per risk factor and its classification, where the weights are provided by the retailer as a risk weights policy. Table 4 shows all 15 permutations of risk factor classifications of a PDS.

Table 4. Phase 2 Combinations and Total Risk Rating Scores

NUMBER OF HIGH (H)	NUMBER OF MEDIUM (M)	NUMBER OF LOW (L)	TOTAL RISK RATING SCORE *(Formula: W_H*H + W_M*M + W_L*L)*
5	0	0	W_H*5
4	0	1	$W_H*4 + W_L$
4	1	0	$W_H*4 + W_M$
3	0	2	$W_H*3 + W_L*2$
3	1	1	$W_H*3 + W_M + W_L$
3	2	0	$W_H*3 + W_M*2$
2	0	3	$W_H*2 + W_L*3$
2	1	2	$W_H*2 + W_M + W_L*2$
2	2	1	$W_H*2 + W_M*2 + W_L$
2	3	0	$W_H*2 + W_M*3$
1	0	4	$W_H + W_L*4$
1	1	3	$W_H + W_M + W_L*3$
1	2	2	$W_H + W_M*2 + W_L*2$
1	3	1	$W_H + W_M*3 + W_L$
1	4	0	$W_H + W_M*4$
0	0	5	W_L*5
0	1	4	$W_M + W_L*4$
0	2	3	$W_M*2 + W_L*3$
0	3	2	$W_M*3 + W_L*2$
0	4	1	$W_M*4 + W_L$
0	5	0	W_M*5

Table 4 shows the total risk rating score obtained by a PDS which is computed based on the formula: $W_H*H + W_M*M + W_L*L$ where W_i represents the weights assigned by the retailer to i = high (H), medium (M), and low (L) risk factor levels respectively. Additionally, H, M, and L represents the total number of risk factors with high, medium, and low risk classifications respectively. The total risk rating score has respective risk classification weights for Low, Medium, High risk classifications, which are to be set by the retail store for calculation. The PDS items are ranked in descending order based on their total risk rating scores with higher risk rating scores being prioritized for management intervention. Using the proposed potential dead stock classification and prioritization framework, validation was performed for multiple data sets to check the consistency and validity of the results per run and tested with the t-test for significance for consistent results.

4. Results and Discussion

To test the proposed potential dead stock framework, hypothetical data were generated for validation, which is assumed to have been acquired from the ERP system of a retail store. The variables with generated hypothetical data per SKU included Annual Demand, Average Inventory, Actual ARL, Days Inventory Policy, Unit Product Cost, Unit Profit Margin, Case Volume, and their intervals as the retailer's policy thresholds. There were three (3) product types considered in the data set, consisting of Consumer Goods (CG), Electronic Items (EL), and Furniture and Appliances (FA). These were selected since they represent the typical fast and slow-moving items in the retail environment for the validation of the framework. In addition, these were used for the item coding to represent each SKU. There are 100 SKUs considered in a data set, where there are 35 CG, 40 EL, and 25 FA. Once the data set has been generated, the first phase, classification phase, was applied to the data set. Table 5 shows the classification phase results.

Table 5. Phase 1: Classification Results

PRODUCT TYPE	%PDS	%DS	%NDS	TOTAL
Consumer Goods (CG)	17.14%	8.57%	74.29%	100.00%
Electronic Items (EL)	10.00%	7.50%	82.50%	100.00%
Furniture and Appliance (FA)	36.00%	8.00%	56.00%	100.00%
All product types	19.00%	8.00%	73.00%	100.00%

Based on the classification phase results, majority of the SKUs generally have more NDS, which are not to be considered for management intervention. However, these classified NDS must still be regularly monitored for another period as results. The PDS items are to be identified and only used for the prioritization phase. The validation for the prioritization phase considered three (3) scenarios. These were selected to compare each result to another scenario and identify the most discriminating scenario that considers the best combination of risk factors for the prioritization phase. Primarily, the PDSI and PMV risk factors were selected since these are the least valuable risk factors. However, to validate this, these were compared to the results if all the risk indicators are considered. The scenarios for the total risk score rating are as follows:

1. Considers all the risk indicators;
2. Does not consider the PDSI risk indicator; and
3. Does not consider the PDSI and PMC risk indicators.

Table 6. Phase 2: Prioritization Results (All Product Types)

PRODUCT TYPE	PRODUCT CODE	SCENARIO RANKS							
		$W_L = 9, W_M = 3, W_H = 1$				$W_L = 10, W_M = 4, W_H = 1$			
		ALL RISK FACTORS	PCV, PSV, PMV, & PDSI	PCV, PSV, & PMV	PCV & PSV	ALL RISK FACTORS	PCV, PSV, PMV, & PDSI	PCV, PSV, & PMV	PCV & PSV
Consumer Goods (CG)	CG-01	4	4	4	4	4	10	10	4
	CG-02	11	11	11	11	11	11	11	11
	CG-06	7	7	7	7	7	3	3	7
	CG-29	6	6	5	6	4	4	5	5
	CG-30	8	8	8	8	8	4	4	8
	CG-33	10	10	10	10	10	10	10	10
Electronic Items (EL)	EL-04	1	1	1	1	1	1	1	1
	EL-11	19	11	11	19	19	11	11	19
	EL-22	3	3	3	3	3	2	2	3
	EL-38	16	16	16	16	16	16	16	16
Furniture and Appliances (FA)	FA-02	13	13	13	13	13	13	13	13
	FA-03	14	14	14	14	14	14	14	14
	FA-05	14	14	14	14	14	14	14	14
	FA-06	17	9	9	17	17	9	9	17
	FA-11	5	5	5	5	5	4	4	5
	FA-12	9	9	8	8	9	7	7	8
	FA-15	18	18	18	18	18	18	18	18
	FA-19	2	2	2	2	2	2	2	2
	FA-23	11	11	11	11	11	11	11	11

Table 6 shows the prioritization results if all product types are ranked together. The weights assigned to the scoring system are based on the concept of House of Quality (HOQ), where weights are 9 for Strong, 3 for Moderate, and 1 for Weak [11]. However, the study modified the weights to 10-4-1 to highlight the importance of the PDSI risk factor by increasing the weight differences from one risk classification to another, as compared to the HOQ weights of 9-3-1.

The performance indicator for the scenarios and risk classification weight sets is the percentage of rank discrimination, measured by the unique rank occurrences. This does not include the SKUs that have the same ranks as other SKUs, since this is focused on the number of times an SKU is assigned with a unique rank. This is to check which scenario and risk classification weight set are best performing. A higher percentage of rank discrimination indicates a better performance as the SKUs have more unique ranks. Having more unique ranks also means that the priority scoring method is able to discriminate among the scores of potential dead stocks in the list. The formula may be seen in Eq. 1. Using the formula presented in Eq. 1, Table 7 shows the summary of the percentage of rank discrimination and their computations.

$$Percentage\ of\ Rank\ Discrimination = \frac{Number\ of\ Unique\ Ranked\ SKUs}{Total\ Number\ of\ SKUs} \tag{1}$$

Based on Tables 6 and 7, a comparison is performed between the two (2) sets of risk classification weights. The 9-3-1 risk classification weight set has a lower percentage of rank discrimination for the resulting prioritization list as compared to the 10-4-1 risk classification weight set, indicating that using the risk classification weights 9-3-1 is less discriminating as more SKUs have the same ranks. This is undesirable since the prioritization phase aims to produce unique ranks to discriminate the prioritization levels more. In addition, the All Risk Indicators and Without PDSI scenarios have the highest percentage of rank discrimination. This implies that considering all the risk indicators or without the PDSI risk factor discriminates the PDS items more compared to other scenarios. Table 8 shows the prioritization results per product type, and Table 9 shows the percentage of rank discrimination per product type across the scenarios and risk classification weight sets. It must be noted that Table 9 follows the same formula in Eq. 1 but is applied per product type.

Table 7. Phase 2: Prioritization Percentage of Rank Discrimination (All Product Types)

PRODUCT TYPE	SCENARIO RANKS							
	$W_L = 9, W_M = 3, W_H = 1$				$W_L = 10, W_M = 4, W_H = 1$			
	ALL RISK FACTORS	PCV, PSV, PMV, & PDSI	PCV, PSV, & PMV	PCV & PSV	ALL RISK FACTORS	PCV, PSV, PMV, & PDSI	PCV, PSV, & PMV	PCV & PSV
All Product Types	$\frac{15}{19}$ = 78.95%	$\frac{13}{19}$ = 68.42%	$\frac{12}{19}$ = 63.16%	$\frac{9}{19}$ = 47.37%	$\frac{14}{19}$ = 73.68%	$\frac{7}{19}$ = 36.84%	$\frac{7}{19}$ = 36.84%	$\frac{6}{19}$ = 31.58%

Table 8. Phase 2: Prioritization Results (Per Product Type)

PRODUCT TYPE	PRODUCT CODE	SCENARIO RANKS							
		$W_L = 9, W_M = 3, W_H = 1$				$W_L = 10, W_M = 4, W_H = 1$			
		ALL RISK FACTORS	PCV, PSV, PMV, & PDSI	PCV, PSV, & PMV	PCV & PSV	ALL RISK FACTORS	PCV, PSV, PMV, & PDSI	PCV, PSV, & PMV	PCV & PSV
Consumer Goods (CG)	CG-01	1	1	1	1	1	4	4	1
	CG-02	5	5	5	5	5	5	5	5
	CG-06	3	3	3	3	3	1	1	3
	CG-29	2	2	1	1	2	1	1	1
	CG-30	4	4	4	4	4	3	3	4
	CG-33	6	6	6	6	6	6	6	6
Electronic Items (EL)	EL-04	1	1	1	1	1	1	1	1
	EL-11	4	4	3	3	4	4	4	3
	EL-22	2	2	2	2	2	2	2	2
	EL-38	3	3	3	3	3	3	3	3
Furniture and Appliances (FA)	FA-02	5	5	5	5	5	5	5	6
	FA-03	6	6	6	6	6	6	6	7
	FA-05	6	6	6	6	6	6	6	7
	FA-06	8	8	3	3	8	8	8	3
	FA-11	2	2	2	2	2	3	3	2
	FA-12	3	3	3	3	3	2	2	3
	FA-15	9	9	9	9	9	9	9	9
	FA-19	1	1	1	1	1	1	1	1
	FA-23	4	4	4	4	4	4	4	5

Table 9. Phase 2: Prioritization Percentage of Rank Discrimination (Per Product Type)

PRODUCT TYPE	SCENARIO RANKS							
	$W_L = 9, W_M = 3, W_H = 1$				$W_L = 10, W_M = 4, W_H = 1$			
	ALL RISK FACTORS	PCV, PSV, PMV, & PDSI	PCV, PSV, & PMV	PCV & PSV	ALL RISK FACTORS	PCV, PSV, PMV, & PDSI	PCV, PSV, & PMV	PCV & PSV
Consumer Goods (CG)	$\frac{6}{6}$ = 100.00%	$\frac{6}{6}$ = 100.00%	$\frac{6}{6}$ = 100.00%	$\frac{6}{6}$ = 100.00%	$\frac{6}{6}$ = 100.00%	$\frac{4}{6}$ = 66.67%	$\frac{4}{6}$ = 66.67%	$\frac{4}{6}$ = 66.67%
Electronic Items (EL)	$\frac{4}{4}$ = 100.00%	$\frac{4}{4}$ = 100.00%	$\frac{2}{4}$ = 50.00%	$\frac{2}{4}$ = 50.00%	$\frac{4}{4}$ = 100.00%	$\frac{4}{4}$ = 100.00%	$\frac{4}{4}$ = 100.00%	$\frac{2}{4}$ = 50.00%
Furniture and Appliances (FA)	$\frac{7}{9}$ = 77.78%	$\frac{7}{9}$ = 77.78%	$\frac{7}{9}$ = 77.78%	$\frac{7}{9}$ = 77.78%	$\frac{7}{9}$ = 77.78%	$\frac{7}{9}$ = 77.78%	$\frac{7}{9}$ = 77.78%	$\frac{5}{9}$ = 55.56%

Based on Tables 8 and 9, similar observations may be found with the results in Tables 6 and 7. However, when the SKUs are ranked per product type, considering all the risk factors discriminate the PDS items more. In addition, using the 10-4-1 risk classification weight set performs better than the 9-3-1 risk classification weight set based on rank discrimination. In addition, seven (7) data sets were generated for the validation of the proposed potential dead stock framework, where data used is hypothetical. The t-test for significance was applied to the results on their number of classified NDS, DS, and PDS, where all results were tested with no significant difference. This implies that all data set results are consistent and valid.

5. Conclusion

The retail industry manages high quantities of various SKUs that tend to accumulate over time if left in the inventory for a long time. The management is then faced with decisions on how to manage these dead stocks as they incur inventory and warehouse costs. However, this is rather a reactive response to dead stock accumulation. In addition, past studies give no focus on systematic management of potential dead stocks to prevent dead stock accumulation from occurring.

This study proposed a standardized framework to identify potential dead stocks in a timely manner for management intervention before the items become dead stocks. The framework proposed consists of two (2) phases: classification and prioritization, where potential dead stocks are identified and ranked on their priority for management intervention. The standardized system aims to utilize the ERP data regularly to generate real-time reports on a ranked list of potential dead stocks for the management to proactively monitor their inventories. These data are used to generate information on the performance indicators to identify the potential dead stocks. The ranking of potential dead stocks is performed in the prioritization phase, which will be used by the retail store for their decision-making and strategic management of these inventories. Risk factors are considered for prioritization to discriminate the ranking accurately. The validation proves that the framework can classify the potential dead stocks accordingly based on the performance indicators and prioritize them well based on the risk factors. It is found that considering more risk factors and a 10-4-1 risk classification weight ranking system rank the potential dead stocks more accurately. Further research may be performed on considering more risk factors in the prioritization phase to better discriminate between rankings, and optimal risk classification weights for each risk factor may be explored. Lastly, the framework is useful for potential dead stock management, but there is potential in exploring mathematical models and algorithms to identify the optimal strategy mix for potential dead stock management per and within the retail store network.

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