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EOQ Model With Imperfect Items and Backorder with Allowable Proportionate Discount using Cross Selling Effects

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***Abstract:** The primary objective of this idea is to create an EOQ model for imperfectly-quality products that takes into account the combined effects of proportionate discount, backorder, clustering with association rule mining, and cross-selling. The ordering policy considering the cross-selling effect was first calculated in this paper. The benefits of cross-selling become especially evident when selling low-quality products. Data mining methods of varying sophistication are used to determine the nature of the connections between the objects. Clustering is used to group together items in the inventory database that are likely to be used together, and then the Apriori algorithm is used to build common item sets from inside each cluster. By the use of cross-selling, the most frequently purchased items are treated as unique entities. In addition, the EOQ of these entities is determined alongside the deficit threshold. Finally, a numerical example is taken into account to verify the results of the suggested work.*

***Keywords:** EOQ, Backorder, Imperfect, Discount, Selling Effects, Cross-Selling*

I. INTRODUCTION

Data mining methods are crucial in the context of business growth and marketing. Data mining is a relatively new method that has sparked a lot of interest in the rapidly expanding information society and business. Data mining is the process of extracting useful information from large data sets. Finding meaningful links among a vast quantity of data items while keeping specifics about a commercial transaction is the focus of association rule mining, a key subfield of data mining. It can aid in a number of business decision-making processes, including cross-selling, inventory control, etc. The cross-selling effect in widely-purchased sets of items has a substantial impact on Economic Order Quantity. In addition, clustering is a method for organising data into sets based on their similarities.

The term "clustering" is used to describe the practise of classifying a set of financial transactions into subsets, each of which shares a set of common characteristics with the others in its cluster. Effective inventory management and EOQ modelling are aided by the use of both association rule mining and clustering methods. In the real world, the sales of one item might have an effect on the sales of another due to their inherent interdependence. The cross-selling effect can be a boon or a bane to their business, depending on the strength of their relationships. Opportunity cost refers to the amount of money that has been lost as a result of this consequence.

Even with careful planning, stringent quality assurance measures, and state-of-the-art production techniques, a small percentage of manufactured goods may be flawed in today's cutthroat marketplace. Items of less-than-perfect quality may not always be flawed, and they may nevertheless have value in some other contexts. In most cases, poor product quality has a direct effect on stock management. It is therefore imperative that all products be inspected thoroughly before to distribution. A number of scholars have proposed several models for estimating the EOQ of low-quality stocks. Much research has been done to demonstrate the EOQ inventory model under a wide variety of settings and presumptions. Traditional EOQ, short for "square root of the EOQ," is a paradigm that provides a bird's-eye view of inventory management and was introduced by Harris. To calculate the cost of damaged goods, the EOQ model was first presented by Porteus [1]. Several EOQ models focusing on flawed products have been developed, sparking interest in the data-mining research community. After 100% screening is complete, one typical EOQ strategy is to sell the defective items at a fixed rate of discount as one batch. This strategy was proposed by Salameh and Jaber [2]. Over the past two decades, industries and organisations have benefited from refinements to the traditional EOQ method.

Because of the shortage and backorder problem, Rezaei was the first researcher to build upon the previous efforts of Salameh and Jaber[3]. He started the cyclical scarcity that arises from faulty production and causes backorders at the start of each cycle. Anand argues that, for some categories of stock, an item is not fundamentally classified into a specified class and is instead impacted by other, comparable or complementary products. The "cross-selling impact" is a well-known term for this type of change in the EOQ of a product. As a result, Agrawal et al. have developed a number of association rule mining techniques to go in this direction.

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Furthermore, Mittal et al [2]. have used association rule mining to construct an EOQ model for defective inventory items with cross-selling impacts. Taking into account the impact of cross-selling, clustering, and association rule mining, Mittal et al[2]. provide a refined model for defective inventory items. Patro et al[4]. have built EOQ models for imperfect products using both crisp and fuzzy data by introducing a proportionate discount and a learning effect in a constrained time horizon in which shortages are tolerated and partial backlogs are acceptable.

In order to create EOQ models with a consistent rate of discount for defectives, following 100% screening, researchers have thus far employed cross-selling effects and association rule mining. The EOQ inventory model uses the profit potential and the optimal order or lot size to account for shortages by applying a proportional rate of discount for defectives present in each lot. This new line of inquiry into inventory modelling is made possible by the fact that the aforementioned works did not incorporate the proportionate discount on imperfect items and cross-selling impacts coupled with data mining approaches for shortages Ruidas[3].

It is being investigated to develop an EOQ model for low-quality goods that takes into account the effects of a proportional discount, the cross-selling effect in the event of shortages, clustering, and association rule mining. Consideration is being given to the case of a transaction database that contains only a small number of items from a frequently occurring item set that are interconnected in some way. According to the provided model, there is an expected fault rate for each batch. To calculate the total profit, a full sweep of the entire lot is performed. The opportunity cost of rethinking the frequently-stocked item model as a collection of items is also investigated. In the end, a numerical example is provided to illustrate the results and the impact of the model's adjustable parameters.

The remainder of this chapter is organized as follows: Section 1.2 is Mathematical Modeling. Section 1.3 provides numerical examples and discussion of results. Section 1.4 contains summary of the proposed work.

II. MATHEMATICAL MODEL

This section introduces proportional discounts in a frequently ordered item set, taking into account cross-selling effects, in order to differentiate between order quantities for items with varying degrees of unsatisfactory quality. There are a number of scenarios in which we take into account the interdependencies between items, where the sale of one item can affect the sale of another. Consider of a scenario in which a common item set has certain objects with connections between them.

Let us consider the given itemset I containing items $I = \{x_1, x_2, x_3, \ldots\ldots, x_n\}$ support of an item is represented as the rate of its occurrences in entire transactions.

$$Support\ (x_1) = Frequency\ (x_1)/No\ of\ total\ Transactions \quad (1.1)$$

Confidence specifies the inter relation among items and defined as conditional probability. $Conf\ (x_1 \rightarrow x_2)$ indicates that frequency of purchasing x_2 when x_1 is purchased.

$$Conf\ (x_1 \rightarrow x_2) = Support\ (x_1 \cup x_2)/Support\ (x_1) \quad (1.2)$$

Rules for the specified association of objects are created using an Apriori method, with support and confidence exceeding the programmer-defined minimum. It's possible to determine the most often purchased things this way. The Apriori method developed by Agrawal et al. is as follows:

Step 1: The first thing it does is go through all of the transactions and tally up how many times each item was purchased. This helps it zero in on the most frequently occurring sets of just one item (L_1)

Step 2: The second step is that it is split into two sections: candidate counting with a priori generation. In order to find, we first utilise L_{k-1} to generate a set of candidate items C_k, and then we search the database and compare the number of items for which each candidate has support to L_k the minimal number of items required to satisfy the criteria $k \geq 2$.

The 'join' and 'prune' operations are carried out with the help of an apriori generating function apriori_gen(). For candidate generation, the 'Join' phase uses join of with, and the 'Prune' step uses the apriori property to get rid of things with rare subsets Kennedy et. Al.[5]

For this study, we take into account transaction clustering as proposed by Wang et al., [6]. Large items here refer to items from a small number of transactions that are similar to one another Ruidas et. Al.[3] What constitutes "support" for an item in cluster is the sum of its sales in that cluster. So, in a cluster, the large items present are all similar, and the support is at least equal to, where is user-defined minimum support; otherwise, the items are all small and therefore heterogeneous. Saving money is a primary motivation for giving this clustering some thought. Further, the 'intra-cluster cost and the inter-cluster cost' are used to calculate the optimal cost-savings strategy. All little goods add up their intra-cluster cost, while all large items in all clusters add up their inter-cluster cost. Clusters are formed and dissolved in this method of clustering on the fly in order to maximise efficiency and reduce costs.

Specifications for the two stages of this clustering algorithm are as follows:

1. First, during the allocation step, all of the transactions are read in order and placed into separate clusters. This cluster could be an already-established one or a brand-new formation.
2. Costs are reduced during the refinement stage.

The effect of cross on items is represented by the corresponding confidence between items. In frequent itemset, the effect of an out-of-stock item x_k on another item i i.e., $I = \{x_1, x_2, x_3, \ldots\ldots, x_n\}$ can be represented as a probability

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$$Prob_{k,i} = \sum_{i=1}^{n} conf(k \rightarrow I(k,i)) \quad (1.3)$$

where $k = 1,2,3,......n$ signifies the set of items i other than the total number of items k that are part of a frequent item-set $f(k,i)$. Hence, we may deduce that.

The lost price of an item k due to cross-selling is an example of its opportunity cost. As such, the relation describes it very well.

$$OC_k = \sum P_c \cdot prob_{k,i} \quad (1.4)$$

where, $P_c =$ cost of each unit item i. In this regard the Probabilistic index a_k is defined as:

$$I_{ndk} = \frac{OC_k + H_x}{OC_k} \quad (1.5)$$

where, H_x = cost of holding item x per unit. The I_{ndk} will be used to implement the concept of opportunity cost in later calculation.

Using the above notation and assumption the following mathematical model for obtaining optimal lot size and the expected shortage level is developed by Patro et al[2].

Under the assumed conditions, the full cycle cost is calculated as follows: $f(L_s, S_L)$ = ordering cost + unit wise purchase cost + screening cost with consideration to cycle wise lot size + carrying cost + Shortage cost

$$f(L_s, S_L) = O_c + P_c L_s + S_c L_s + H_c \times \left(\frac{L_s(1-p) - S_L}{2} t_1 + \frac{pL_s^2}{r}\right) + \frac{S_L B_c}{2} t_2 \quad (1.6)$$

Total revenue cycle wise is calculated by adding total sales of both good and imperfect quality items which is specified as:

$$g(L_s, S_L) = SL_s(1-p) + \sum_{i=1}^{L_s p} \left(S - \left(1 - \frac{L_s p - i}{L_s p}\right)\left(\frac{g(L_s, S_L) - f(L_s, S_L)}{z}\right)\right)$$

The total profit $\pi(L_s, S_L)$ cycle wise is formulated as:

$$\pi(L_s, S_L) = g(L_s, S_L) - f(L_s, S_L)$$

$$\pi(L_s, S_L) = \frac{2SL_s^2 - 2L_s\left(O_c + P_c L_s + S_c L_s + H_c \times \left(\frac{L_s(1-p) - S_L}{2} t_1 + \frac{pL_s^2}{r}\right) + \frac{S_L B_c}{2} t_2\right)}{2L_s + (L_s p + 1)} \quad (1.7)$$

The total profit per unit time $\pi_u(L_s, S_L)$ is formulated as:

$$\pi_u(L_s, S_L) = \frac{\pi(L_s, S_L)}{T}$$

where, $T = \frac{L_s(1-p)}{D}$ and by replacing t_1 and t_2 by $\frac{L_s(1-p) - S_L}{D}$ and $\frac{S_L}{D}$ respectively. Equation 4 can be written as:

$$\pi_u(L_s, S_L) = \frac{2D[SL_s - O_c - P_c L_s - S_c L_s]}{(1-p)(2L_s + L_s p + 1)} - \left[\frac{H_c L_s}{2L_s + L_s p + 1}\{L_s + pL_s - 2S_L\} + \frac{S_L^2(B_c + H_c)}{(1-p)(2L_s + L_s p + 1)}\right] \quad (1.8)$$

As p is the % of defectives, with a known p.d.f., then the Equation 8. $E\pi_u(L_s, S_L)$, is given as follows:

$$E\pi_u(L_s, S_L) = \frac{2D[SL_s - O_c - P_c L_s - S_c L_s]}{(1 - E[p])(2L_s + L_s E[p] + 1)} - \left[\frac{H_c L_s\{L_s + E[p]L_s - 2S_L\}}{2L_s + L_s E[p] + 1} + \frac{S_L^2(B_c + H_c)}{(1 - E[p])(2L_s + L_s E[p] + 1)}\right] \quad (1.9)$$

The optimality condition for the nonlinear problem and the expected total profit per unit time mentioned in Equation 6, is represented by computing the 1^{st} and 2^{nd} partial derivatives of $E\pi_u(L_s, S_L)$ with respect to L_s, S_L

By equating $\frac{\partial ETPU(L_s, S_L)}{\partial L_s}$ and $\frac{\partial ETPU(L_s, S_L)}{\partial S_L}$ to zero, we found:

$$L_s^* = \sqrt{\frac{2DS - 2DP_c - 2DS_c + 4DO_c + 2DO_c E[p]}{2H_c + 2H_c E[p] - 3H_c(E[p]^2) - H_c(E[p]^3) - \frac{2B_c H_c^2(1-E[p])^2}{(B_c + H_c)^2} - \frac{2H_c^3(1-E[p])^2}{(B_c + H_c)^2} - \frac{B_c H_c^2 E[p](1-E[p])^2}{(B_c + H_c)^2} - \frac{H_c^3 E[p](1-E[p])^2}{(B_c + H_c)^2}}} \quad (1.10)$$

$$S_L^* = \left(\frac{H_c L_s(1 - E[p])}{B_c + H_c}\right) \quad (1.11)$$

$$IM = L_s - S_L \quad (1.12)$$

The maximum level of inventory is obtained by putting the value of Equation 10 and Equation 11 in Equation 12 and is given as:

$$IM^* = \frac{L_s^*(B_c + H_c E[p])}{B_c + H_c} \quad (1.13)$$

After obtaining the 1^{st} and 2^{nd} principal minor of H, at point (L_s^*, S_L^*) the Hessian Matrix H is negative definite, that indicates existence of unique values of L_s^* (Equation 10) and S_L^* (Equation 4.11) that maximize Equation 4.9.

III. NUMERICAL RESULTS

We consider the following example for analysis of the present work. We use the values for the parameters needed for analysing the above inventory situation according to Mittal et al.[2] , Patro et al.,[2] , which are as follows:

min_sup=60%, min_conf=75%, D =50,000 units/year, O_c=100/cycle, H_c= \$5/unit/year, r =1unit/min, S_c =0.5/unit, P_c =25/unit, B_c=\$ 20/unit, S = \$50/unit, w =175 200 units/year Also, we assume the defective proportion p is uniformly distributed with p.d.f. The expected values present in the model are given as follows:

$E[p] = 0.02$ and $E[1/(1-p)] = 1.02055$

Let us consider the database set D and the inventory item-set,

$I = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$.

Each row indicates an inventory transaction in the set, $itd = \{itd1, itd2, itd3, itd4, itd5, itd6\}$, that is given in Table 4.1.

Table 1. An Inventory Transaction Database

itd	Items
itd1	x_1 x_2 x_3
itd2	x_1 x_2 x_3 x_4
itd3	x_1 x_2 x_3 x_5
itd4	x_1 x_2 x_6
itd5	x_4 x_7 x_8
itd6	x_4 x_7 x_9

An apriori algorithm is utilised to create the underlying association rules between these exchanges. Table 1.2 shows the values of the inventory policy parameters used to determine the opportunity cost of various goods. We assume a minimum support level of 60% (total number of transactions = 6) in the inventory transaction database. In this case, the calculation yields a sizable item, and at least four purchases are required. We have done the same kind of calculations for each cluster.

Table 2. Parameter values for inventory policy

Item	D	P_c	H_c	Selling Price (Good Items)	Selling Price (Imperfect Items)
x_1	50,000	30.00	3	60.00	25.00
x_2	40,000	20.50	2	40.00	17.00
x_3	40,000	45.52	4	60.00	40.00
x_4	50,000	50.00	5	90.00	45.00
x_5	50,000	45.52	4	70.00	40.00
x_6	40,000	40.00	4	65.00	35.00
x_7	50,000	34.00	3	60.00	30.00
x_8	40,000	32.00	3	50.00	27.00
x_9	50,000	23.00	2	40.00	18.00

Details of all clusters are given in Table 1.3. Therefore, cluster C_2 is considered as cost obtained is minimum in comparison to cluster C_1 and C_3. So, the given transaction database is clustered into two clusters as, $C_1 = \{itd1, itd2, itd3, itd4\}$ and $C_2 = \{itd5, itd6\}$. Then apriori algorithm is applied on both clusters to obtain frequent sets. $\{x_1, x_2, x_3\}$ and $\{x_4, x_7\}$ are the most frequent itemsets in clusters C_1 and C_2 respectively. Confidence of items in both frequent itemsets are calculated with Equation 1.2, and given in Table 1.4.

Table 3: Clustering details

Clustering	Large	Small	Intra	Inter	Cost
C_1 = {itd1, itd2, itd3, itd4, itd5, itd6}	$L_1 = \{x_1, x_2\}$	$S_1 = \{x_3, x_4, x_5, x_6, x_7, x_8, x_9\}$	7	0	7
C_2= { C_1={itd1, itd2, itd3, itd4}, C_2={itd5, itd6} }	$L_1 = \{x_1, x_2, x_3\}$ $L_2 = \{x_4, x_7\}$	$S_1 = \{x_4, x_5, x_6\}$ $S_2 = \{x_8, x_9\}$	5	0	5
C_3= { C_1 = {itd1, itd}, C_2 = {itd3, itd4}, C_3 = {itd5, itd6} }	$L_1 = \{x_1, x_2, x_3\}$ $L_2 = \{x_1, x_2\}$ $L_3 = \{x_4, x_7\}$	$S_1 = \{x_4\}$ $S_2 = \{x_3, x_5, x_6\}$ $S_3 = \{x_8, x_9\}$	6	2	8

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Table 4. Confidence of frequent item-set in cluster C_1 and cluster C_2

For Cluster C_1		For Cluster C_2	
Items	**Confidence**	**Items**	**Confidence**
$x_1 \to x_2$	100	$x_4 \to x_7$	100
$x_1 \to x_3$	75	$x_7 \to x_4$	100
$x_1 \to x_2 \cup x_3$	75		
$x_2 \to x_1$	100		
$x_2 \to x_3$	75		
$x_2 \to x_3 \cup x_4$	75		
$x_3 \to x_1$	100		
$x_3 \to x_2$	100		
$x_3 \to x_1 \cup x_2$	100		

Then the opportunity cost in the frequent itemset can be calculated by formulae given in Equation 4.

Opportunity cost of item x_1 =

$$OC_{(x_1)} = C_{x_1}.conf(x_1 \to x_1) + C_{x_2}.\{conf(x_1 \to x_2) + conf(x_1 \to x_2 \cup x_3)\} + C_{x_3}.\{conf(x_1 \to x_3) + conf(x_1 \to x_2 \cup x_3)\}$$

$$= 30 \times 1 + 20.50 \times \{1 + 0.75\} + 45.52 \times \{0.75 + 0.75\}$$
$$= 30 + 35.875 + 68.28$$
$$= 134.155$$

Similarly, $OC_{(x_2)} = 141.28$, $OC_{(x_3)} = 146.52$, $OC_{(x_4)} = 84$ and $OC_{(x_7)} = 84$

After substituting the values of opportunity costs of x_1, x_2, x_3, x_4, x_7, we get I_{nd} (index) for the frequent items of both clusters C_1 and C_2.

$$I_{nd}(x_1) = \frac{H_r + OC_{(x_1)}}{OC_{(x_1)}} = 1.07534221, \quad I_{nd}(x_2) = \frac{H_r + OC_{(x_2)}}{OC_{(x_2)}} = 1.070781427,$$

$$I_{nd}(x_3) = \frac{H_r + OC_{(x_3)}}{OC_{(x_3)}} = 1.06825007, \quad I_{nd}(x_4) = \frac{H_r + OC_{(x_4)}}{OC_{(x_4)}} = 1.11904762 \text{ and}$$

$$I_{nd}(x_7) = \frac{H_r + OC_{(x_7)}}{OC_{(x_7)}} = 1.11904762$$

The optimum value of item x_1 is:

$$EOQ(x_1) = x_1^* = 2078.76 \ units$$

Modified EOQ of item x_1 is:

$$EOQ(x_1) = x_1^*.\sqrt{I_{nd}(x_1)} = 2078.76 \times 1.036987083 = 2155.647269$$

Similarly, for items x_2, x_3, x_4, x_7 can be determined as:

$$EOQ(x_2) = x_2^*.\sqrt{I_{nd}(x_2)} = 2178.76 \times 1.034785691 = 2254.425498,$$

$$EOQ(x_3) = x_3^*.\sqrt{I_{nd}(x_3)} = 1640.097265,$$

$$EOQ(x_4) = x_4^*.\sqrt{I_{nd}(x_4)} = 1809.474388$$

and $EOQ(x_7) = x_7^*.\sqrt{I_{nd}(x_7)} = 2179.944201$

To analyze the present work, above numerical example is considered. First Clustering algorithm is applied to the inventory transaction database to obtain homogeneous clusters. Then apriori algorithm is used on clustered data to generate association rules and find frequent item sets. Opportunity cost is formulated to find EOQ for imperfect quality items. Further, lot size, expected total profit unit wise, shortage level, and maximum inventory level are calculated. Four different cases are considered and are represented in Table 1.5, 1.6, 1.7, 1.8. Table 1.5 for different values of demand and holding cost, Table 6 for constant demand, Table 1.7 for constant holding cost, and Table 1.8 for constant values of demand and holding cost respectively.

Table 5. For different vlues of demand and holding cost

Items	OC_k	L_s	EOQ	$E\pi_u(L_s,S_L)$	S_L	$IM = L_s - S_L$
x_1	134.155	2078.76	2155.647269	1484660	265.72	1813.04
x_2	141.28	2178.76	2254.425498	763795	194.097	1984.543
x_3	146.52	1586.84	1640.097265	559549	259.104	1327.736
x_4	84	1710.52	1809.474388	1988340	335.262	1375.258
x_7	84	2060.73	2179.944201	1282650	263.415	1797.315

Table 6. Demand is Constant

Items	L_s	EOQ	$E\pi_u(L_s,S_L)$	S_L	$IM = L_s - S_L$
x_1	2078.76	2155.647269	1484660	265.72	1813.04
x_2	2435.8	2520.530986	955277	217.008	2218.792
x_3	1774.14	1833.683397	700151	289.776	1484.364
x_4	1710.52	1808.474388	1988340	335.262	1375.258
x_7	2060.73	2179.944201	1282650	263.415	1797.315

Table 7. Holding cost is constant

Items	L_s	EOQ	$E\pi_u(L_s,S_L)$	S_L	$IM = L_s - S_L$
x_1	1674.73	1736.673378	1483330	328.247	1346.483
x_2	1463.56	1514.470946	761828	286.858	1176.702
x_3	1446.84	1495.398608	559027	283.581	1163.259
x_4	1710.52	1809.474388	1988340	335.262	1375.258
x_7	1660.2	1756.243352	1281330	325.399	1334.801

Table 8. Both demand and holding cost are constant

Items	L_s	EOQ	$E\pi_u(L_s,S_L)$	S_L	$IM = L_s - S_L$
x_1	1674.73	1736.673378	1483330	328.247	1346.483
x_2	1636.31	1693.230174	953077	320.717	1315.593
x_3	1617.62	1671.910299	699567	317.054	1300.566
x_4	1710.52	1809.474388	1988340	335.262	1375.258
x_7	1660.2	1756.243352	1281330	325.399	1334.801

IV. MANAGERIAL INSIGHTS

During the analysis we observed that when the rate of discount increases, the number of defectives decreases. Either demand is constant or variable lot size and expected profit unit wise increases. Either holding cost is constant or both demand and holding cost unit wise are constant, lot size decreases.

V. SUMMARY

This chapter has covered an EOQ inventory model with cross-selling effect and a proportional discount for defective items with shortages. The rate of discount is shown to rise as faulty counts fall. Once the received lot has been thoroughly inspected, the defective items are packaged together and sold at a discounted rate. Clustering with an apriori algorithm is taken into account for the inventory transaction database, which results in more association rules being developed and selected, leading to a higher net profit. When examining our issue, we took into account four distinct scenarios. It has been noted that the new opportunity cost may have a negligible influence on the lot size due to the cross-selling effect in a frequently purchased itemset. Additionally, we discovered that when both demand and holding cost are variable values, the overall profit and lot size are larger than when demand is fixed. It has been seen once more that lot sizes shrink under the conditions of either constant holding cost or constant demand and unit wise holding cost. This study has the potential to shed light on how to refine the EOQ model for two distinct classes of low-quality products by exploiting the cross-selling effect in conjunction with various classification strategies.

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