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Artificial Intelligence in Market Segment Portfolio for Profit Maximization

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This paper proposes an approach to select a market segment portfolio to maximize overall profit. The study first uses artificial intelligence algorithms to select the market segments with high profitability. The mathematical programming model is then used to identify the most profitable market segment portfolio. The single-objective programming model is used to find the optimal profit for the baseline condition, and a sensitivity analysis is performed to understand the impact of the variable changes on the results. Then, a multi-objective programming model helps to identify the best profit when the evaluated items reach extreme values. A sensitivity analysis is conducted to reveal the impact of the variable changes on the results. The above results are compared with those of the scoring method. It is found that the artificial intelligence algorithm combined with mathematical programming models can indeed find the market segmentation portfolio with better profits than the conventional methods.

Keywords: *Artificial Intelligence; Mathematical Programming; Market Segments; Segment Portfolio; Profit Maximization.*

Introduction

It is almost impossible for a company to launch a product that satisfies all customers because everyone's preferences are different and customers have different requirements for the same product. Therefore, the best way is to identify a group of customers with common preferences—ensuring that the number of customers is large enough for the company to make long-term profits—and then the company gives full play to its core competence to develop products and services that can satisfy these customers. The above process of identifying target customers is called market segmentation (Gomez-Suarez *et al.,* 2020). It is used to divide a large market with mixed demand into several small markets with the same demand and then to select the small markets in which the company can make a profit and serve. These relatively small markets are called market segments.

Often, companies need to not only know which market segments can bring significant profits to the company but also find a combination of market segments that can maximize the overall profit from the many profitable market segments (Gregory & Glytin, 1998). Because each company has limited resources, be it financial or human, it is usually not possible to take care of all profitable market segments simultaneously, even if they all have the potential to generate profits for the company. To divide the entire market into several market segments, one can use questionnaires to understand the differences in customers' preferences for products—in terms of geographic, demographic, psychological, and behavioral variables—and then use statistical analysis methods, such as cluster analysis and discriminant analysis, to summarize the differences in customers' preferences for products under different variables. Customers with the same preferences are grouped, and thus, market segments are formed (Goyat, 2011).

After dividing several market segments, the next step is to pick the ones that are relatively more profitable. This is called market segment targeting (Dibb & Simkin,1991). Traditionally, the scoring method was most commonly used because it was simple and easy to understand. Companies would select several evaluation items for market segmentation and their relative weights. Then, the committee would score the candidate market segments, and the scores would be multiplied by the weights. After, they would all be added up to get the total score of each market segment. Finally, the market segments are selected in order according to the total score (Wright Associates, 2010).

The problem with this method is that human judgment can easily lead to errors, either by missing the market segment that should be selected or by selecting a market segment that should not, resulting in lower profitability or even loss for the company (Zanjirdar, 2020). To solve this problem, this study for the first time uses artificial intelligence to select market segments that can be profitable and have a high success rate and then employs mathematical programming to find the market segment portfolio with the largest overall profit. Single-objective mathematical programming is used to find the maximum profit under baseline conditions; a sensitivity analysis is conducted to understand the changes in profit under different variables. Then, multi-objective mathematical programming, with the support of the fuzzy theory, is used to find the maximum profit when all evaluation items reach the extreme value. Finally, the results of the single-objective and multi-objective mathematical programming are compared with the portfolio obtained by the conventional scoring method.

Literature Review

This section examines the past literature related to the topic of this study, including the market segment, market portfolio and artificial intelligence.

Market Segment

The demand of the market comes from consumers' preferences for products. However, the consumers' preferences are so diverse that it is totally impossible for a company to introduce a product or service to meet all consumers' expectations or even to make them all customers. Therefore, enterprises should probably make efforts to identify customers with similar preferences among all consumers, understand their needs in-depth, and then launch products or services that can meet their needs (Gomez-Suarez *et al.,* 2020). This process is called market segmentation, which is used to divide a relatively large market with different needs into several relatively small markets with the same needs. Enterprises may, according to their own resources and capabilities, select several market segments with the same demand where they can make a profit and compete and, then, launch products and services that meet the demand.

The method of segmenting markets usually employs questionnaires to obtain information on customer needs, including demographic, psychographic, geographic, and behavioral variables. Then, through statistical analysis, customers with similar consumption patterns are grouped into the same categories (Smeureanu *et al.,* 2013). These categories are finally market segments. Then one or several appropriate market segments are selected from among them.

There are several studies exploring market segmentation. Gopalan (2007) proposed a Z-ranking architecture, combined with customer portfolio management technology, which allowed companies to use limited resources to segment the customers who could bring the highest value to the company. Sackmann *et al*. (2010) constructed an e-commerce model that could determine the best combination of customer segmentation while considering both risk and profit. Goyat (2011) examined the method of market segmentation, believing that demographic and psychological variables were most often used to segment the market. Bergemann and Bonatti (2011) established a model to describe the phenomenon of competitive equilibriums in the advertising market and to evaluate the impact of market choices. Almgren (2014) used market size, market growth, market stability, and competition to select market segments. Liu et al. (2019) proposed a multi-criteria decision making approach for market segmentation that combines preference analysis and segmentation decision. Zhou (2020) developed a market segmentation method to identify and explore existing and potential aviation markets. Kalam (2020) explored the strategy of market segmentation and positioning when exploring the impact of distinguishing market segments on the success or failure of business operations. Gunay and Gokasar (2021) examined the effect of destination type of airport access mode choice using multinomial logit and mixed logit models, and suggested that different transportation policies may need to be introduced for domestic and international traveler segments.

Market Portfolio

Literature related to the market portfolio focused largely on the financial industries, which implies that a method suitable for the market portfolio of products other than financial institutions is nonexistent and needs to be developed.

Dominguez and Page (1984) concluded that a bank's lasting retail growth and profitability depend significantly on its ability to attain a balanced portfolio of three high profit market segments. Varadarajan (1990) proposed three constructs, the market share multiplier, the physical volume multiplier and the dollar volume multiplier to analyze the product portfolio, and discover the relationship between market share, market size, market growth rate, product sales volume and product sales growth rate. Gregory and Glytin (1998) believed that market segmentation should be selected from the perspective of combination. Elliott and Glytin (1998) proposed a portfolio based approach to select segments based on their value to the financial organization both in the present and over the medium-term future. Pischedda et al. (2010) indicated that grouping property assets in segments maximizes the variance of returns across segments but minimizes that of individual assets in each segment. Asiedu (2016) examined the use and impact of market segmentation practices on the performance of banks, and found that segmentation practices have greatly affected the performance of the selected banks. Zanjirdar (2020) reviewed the literature of portfolio selection and optimization methods according to the problem types.

Artificial Intelligence

Artificial intelligence is a science that uses algorithms to allow computers to learn human thinking skills. It generally includes machine learning and deep learning. Machine learning is divided into four areas: (1) supervised learning: machine learning with marked results in the goal column, (2) semi-supervised learning: machine learning with marked results in some goal columns and no marked results in others, (3) unsupervised learning: learning without marked results in the goal column, and (4) reinforcement learning: learning with positive and negative feedback on the interaction process with the environment to maximize the learning benefit. Deep learning refers to a neural network-like learning approach with multiple, hidden layers.

Artificial intelligence has been used extensively in product marketing and has yielded tremendous results. For example, a Harley Davidson dealership in New York, U.S. used artificial intelligence to replace the judgment of analysts and increased their sales 30-fold (Power, 2017). Ascarza (2018) believed that using artificial intelligence to find high-risk disloyal customers is not necessarily what companies should try to save, subverting the general perception of acquiring customers. Jarek and Mazurek (2019) discussed the application of artificial intelligence in product marketing. Davenport *et al*. (2019) proposed a multi-dimensional architecture that can help understand the impact of artificial intelligence on the industry. Davenport *et al*. (2020) proposed a framework to understand how artificial intelligence affects product marketing, including the level of intelligence, the type of work, and whether artificial intelligence should be built into marketing robots. He also suggested that effective artificial intelligence should assist rather than replace personnel. Verma *et al*. (2021) analyzed 1,580 papers from 1982 to 2020 in an attempt to summarize the future development and research directions of artificial intelligence in product marketing. Huang and Rust (2021) developed a three-stage architecture that uses artificial intelligence to assist in planning marketing strategies, including mechanical artificial intelligence, thinking artificial intelligence, and sensory artificial intelligence.

Research Methodology

This study first used supervised algorithms of artificial intelligence to build a market segmentation model. Next, this model helped to predict the market segments with higher success rates. Finally, a mathematical programming model determined which combinations of market segments with high success rates can maximize the overall profitability of an enterprise given the resource and risk constraints.

Artificial Intelligence

(1) Screening market segments with artificial intelligence First, the artificial intelligence algorithm was used to train data sets formed by market segments that have been explored in the past. The main purpose was to summarize the past performance experience in these market segments to build a model to determine the performance of the products in these market segments.

(i) Training dataset

To build a market segmentation selection model using artificial intelligence requires a training data set. If a company does not have experience in marketing products in certain market segments, the training data set can be obtained through market research, rival information, competitive intelligence analysis, and other methods. Table 1 shows the 19 training data sets for market segments, in which the market size unit is one million customers. The risk is level 1 to 8. The smaller the level, the lower the risk. The degree of competition is 0 to 1. The smaller the value, the less competition. Market growth is 1 to 7, and the smaller value the smaller the growth rate. The profit is the actual value of the expected profit, in millions of U.S. dollars. The cost is the expected cost, and the unit is millions of dollars. The class on the far right is the performance result of the market segments, where "yes" represents that the market segmentation performance was good, and "no" indicates that it was not good.

Table 1

Market Segmentation Training Data Set

No	Size	Risk	Competition	Growth	Profit	Cost	class
1	10	7	0.4	3	31	18	no
2	30	3	0.6	6	50	22	yes
3	25	6	0.7	3	18	11	no
4	15	4	0.4	7	48	21	yes
5	32	4	0.5	6	56	22	yes
6	19	1	0.3	6	60	24	yes
7	28	5	0.6	1	24	15	no
8	31	4	0.3	6	40	13	yes
9	18	3	0.4	7	56	21	yes
10	26	5	0.5	5	26	17	yes
11	40	8	0.7	3	31	18	no
12	39	6	0.7	6	50	22	yes
13	45	6	0.6	3	18	11	no
14	44	7	0.5	7	48	21	yes
15	59	8	0.2	6	56	22	yes
16	60	5	0.1	6	60	24	yes
17	75	4	0.7	1	24	15	no
18	38	6	0.8	6	40	13	yes
19	48	7	0.9	7	56	21	yes

(ii) Establishing the market segmentation model

Then, the artificial intelligence algorithms were used to model the market segment data in Table 1. This study uses three algorithms to build the prediction models, including Naivebayes, Logistic, and J48 and Table 2 lists the results. The accuracy of the Naivebayes algorithm is 94.7368 %, with a Kappa value of 0.8834 and an RMSE of 0.2084; the accuracy of the Logistic algorithm is 100 %, with a Kappa value of 1 and an RMSE of 0. Finally, the accuracy of the J48 algorithm is also 100 % with a Kappa value of 1 and an RMSE of 0. Therefore, the accuracy of the model is the lowest for the Naivebayes algorithm, and Logistic and J48 are tied for the highest accuracy.

Table 2

Summary of the Accuracy of the Three Algorithms

	NaiveBayes (94.7368 %)		**Logistic (100 %)**		**J48 (100 %)**	
	Kappa	**RMSE**	**Kappa**	**RMSE**	**Kappa**	**RMSE**
	0.8834	0.2084	1	0	1	0
	yes	no	yes	no	yes	no
True positive	0.923	1.000	1.000	1.000	1.000	1.000
False positive	0.000	0.077	0.000	0.000	0.000	0.000
Precision	1.000	0.857	1.000	1.000	1.000	1.000
Recall	0.923	1.000	1.000	1.000	1.000	1.000
F measure	0.960	0.923	1.000	1.000	1.000	1.000
MCC	0.889	0.889	1.000	1.000	1.000	1.000
ROC area	1.000	1.000	1.000	1.000	1.000	1.000
PRC area	1.000	1.000	1.000	1.000	1.000	1.000

(iii) Predicting the performance of market segments

After establishing the market segmentation models using the three algorithms, these models can then be used to predict the performance of the new market segments. Table 3 is the test data set formed by the candidate market segment data. From the 12 new market segments, the company may select the ones from which it expects good performance to launch its products.

Table 3

Test Data Set of Selected Market Segments

No	**Size**	**Risk**	**Competition**	**Growth**	**Profit**	**Cost**	**Class**
1	85	7	0.5	5	56	17	**?**
2	73	8	0.4	3	76	18	**?**
3	61	6	0.8	6	89	22	**?**
4	77	9	0.9	3	23	11	**?**
5	88	6	0.5	7	45	21	**?**
6	89	7	0.2	6	93	22	**?**
7	90	6	0.4	6	23	24	**?**
8	65	6	0.6	1	48	15	**?**
9	55	8	0.1	6	83	13	**?**
10	45	7	0.9	7	50	21	**?**
11	87	8	0.3	5	29	17	**?**
12	96	3	0.5	4	45	25	**?**

Table 4 summarizes the results of the performance prediction using the above-mentioned three algorithms of the performance model for each of the candidate market segment's test data sets in Table 3. In Table 4, the percentage figures underneath "Algorithm" refer to the accuracy of the relevant model, the "Forecast" column indicates the performance prediction of the algorithm, and the "Probability" column shows the likelihood of the performance prediction status.

Table 4

Prediction Results of the Three Algorithms

No.	**Algorithm**						**Majority**
	NaiveBayes (94.7368 %)		**Logistic (100 %)**		**J48 (100 %)**		
	Forecast	**Probability**	**Forecast**	**Probability**	**Forecast**	**Probability**	
1	yes	1.000	yes	1.000	yes	1.000	yes
2	yes	1.000	no	1.000	no	1.000	no
3	yes	1.000	yes	1.000	yes	1.000	yes
4	no	1.000	no	1.000	no	1.000	no
5	yes	1.000	yes	1.000	yes	1.000	yes
6	yes	1.000	yes	1.000	yes	1.000	yes
7	yes	0.996	yes	1.000	yes	1.000	yes
8	no	1.000	no	1.000	no	1.000	no
9	yes	1.000	yes	0.963	yes	1.000	yes
10	yes	1.000	yes	1.000	yes	1.000	yes
11	no	0.813	yes	1.000	yes	1.000	yes
12	yes	0.999	yes	1.000	yes	1.000	yes

From Table 4, we can find that Naivebayes predicts that the performance of market segments 4, 8, and 11 will be bad, and the performance of other market segments should be good, whereas Logistic predicts that the performance of market segments 2, 4, and 8 will be bad, and the performance of the other ones should be good. J48 also predicts bad performance for market segments 2, 4, and 8 and good performance for the others. Judging the combined performance predictions of the three algorithms, the majority decision reveals the results of the comprehensive judgment of the good market segments, as shown in Table 5.

Table 5

Result of Market Segments' Comprehensive Judgment

No	Size	Risk	Competition	Growth	Profit	Cost	Class
1	85	7	0.5	5	56	17	yes
3	61	6	0.8	6	89	22	yes
5	88	6	0.5	7	45	21	yes
6	89	7	0.2	6	93	22	yes
7	90	6	0.4	6	23	24	yes
9	55	8	0.1	6	83	13	yes
10	45	7	0.9	7	50	21	yes
11	87	8	0.3	5	29	17	yes
12	96	3	0.5	4	45	25	yes

From Table 5, we can see that these market segments can be profitable for companies, but each company has limited resources. If a company's resources cannot take care of so many market segments simultaneously, then that company must determine which market segments should be chosen to maximize the overall profitability of the company and to keep the cost within the budget and the risk within the acceptable threshold. This question is the subject of the next section.

Mathematical Programming

This section divides the methods into single-objective mathematical programming and multi-objective mathematical programming for comparison.

(i) Single-objective mathematical programming

Assuming that the company wants to select a group of market segments with the highest overall profit from the segmentation results in Table 5 while keeping the other conditions within an acceptable range, the decision to select the best group of market segments can be expressed as a single-objective mathematical programming model as seen in Equation (1).

$$\begin{aligned}
\text{Max} \quad & \sum_{i=1}^{n} x_i p_i \qquad (1)\\
\text{S.T.} \quad & \sum_{i=1}^{n} x_i s_i \geq S\\
& \sum_{i=1}^{n} x_i r_i \leq R\\
& \sum_{i=1}^{n} x_i com_i \leq C\\
& \sum_{i=1}^{n} x_i g_i \geq G\\
& \sum_{i=1}^{n} x_i c_i \leq B\\
& x_i = \begin{cases} 1 & selected \\ 0 & otherwise \end{cases}, \text{ i=1, 2, …, n}
\end{aligned}$$

Where s_i denotes the market size i,
r_i is the risk of the market i,
com_i is the competition level of the market i,
g_i is the growth rate of the market i,
p_i is the expected profit of the market i,
c_i is the estimated cost of the market i, and
S, R, C, G, and B denote the threshold of the total market size, risk, competition, growth, and budget.

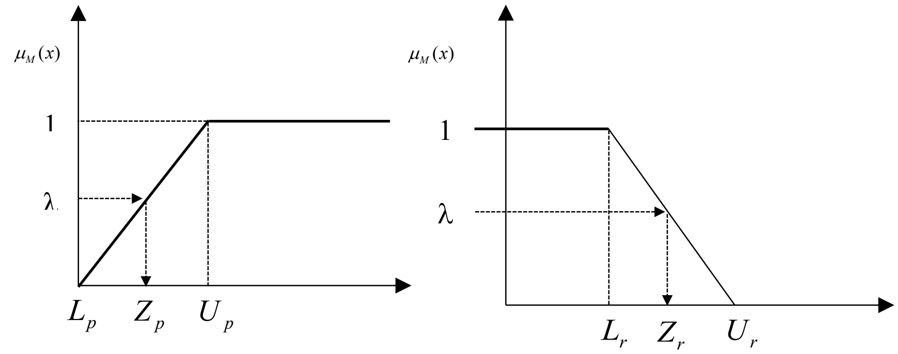
(ii) Multi-objective mathematical programming

If a company chooses the best combination of market segments, and hopes that the selected market segments will not only maximize the overall profit but also maximize the sum of the market segment size, minimize the sum of the risk, minimize the sum of the competition, maximize the sum of the growth, and minimize the sum of the cost. At this point, choosing the best market segment portfolio becomes a multi-objective decision, as shown in Equation (2).

$$\begin{aligned}
Max \quad & \sum_{i=1}^{n} x_i P_i \qquad (2)\\
Max \quad & \sum_{i=1}^{n} x_i s_i\\
Min \quad & \sum_{i=1}^{n} x_i r_i\\
Min \quad & \sum_{i=1}^{n} x_i com_i\\
Max \quad & \sum_{i=1}^{n} x_i g_i\\
Min \quad & \sum_{i=1}^{n} x_i c_i\\
\text{S.T.} \quad & \sum_{i=1}^{n} x_i s_i \geq S\\
& \sum_{i=1}^{n} x_i r_i \leq R\\
& \sum_{i=1}^{n} x_i co_i \leq C\\
& \sum_{i=1}^{n} x_i g_i \geq G\\
& \sum_{i=1}^{n} x_i c_i \leq B\\
& x_i = \begin{cases} 1 & selected \\ 0 & otherwise \end{cases}, \; i = 1, 2, \ldots, n
\end{aligned}$$

Equation (2) must be transformed into a single-objective form before it can be solved. This study applies the concept of membership function in fuzzy theory to convert six objectives into a single objective, and then the extreme values of these six objectives can be found simultaneously by maximizing this single objective. Among the six objectives, profit, market size, and growth are expected to be maximized, whereas risk, competition, and cost are minimized; therefore, both the maximized and minimized fuzzy membership functions can be used, respectively.

If taking profit maximization and risk minimization as an example, the λ in Figure 1 is the variable to be maximized; the closer its value is to 1, the closer the profit is to the upper bound U_p, and the closer the risk is to the lower bound L_r. The upper bound of the six objectives is Case 8 in Table 7, which is the sum of the six items when all market segments are selected. For example, the sum of the risks of all market segments is the upper bound of the risk objective. The lower bound is the individual sum of the six items in Case 1 in Table 7, i.e., the individual sum of the six items for the market segments selected for the base case; for example, the sum of the risks in market segments 1, 3, 5, 6, 7, and 11 for the base case is the lower bound value of the risk objective. The reason for using the base case as the lower bound is because it has the lowest profit value of 335.



(a) Maximized membership function (Profit) (b) Minimized membership function (Risk)

Figure 1. Fuzzy Membership Function

From the comparison of the two triangles in Figure 1(a), one can obtain $\frac{Z_p - L_p}{U_p - L_p} = \frac{\lambda}{1}$, therefore, $Z_p - L_p = \lambda(U_p - L_p)$, because $0 \le \lambda \le 1$, Equation (3) can be obtained, and it can be used for other objectives if they are maximized.

$$-Z_p + \lambda(U_p - L_p) \le -L_p \tag{3}$$

Similarly, the risk objective can be obtained by Equation (4), and it can be used for other objectives as long as they are minimized:

$$Z_r + \lambda(U_r - L_r) \le U_r \tag{4}$$

Figure 2 graphically depicts the multi-objective model using fuzzy membership function. It can be seen that when the value of λ approaches 1, all objectives will approximate to their extreme values.

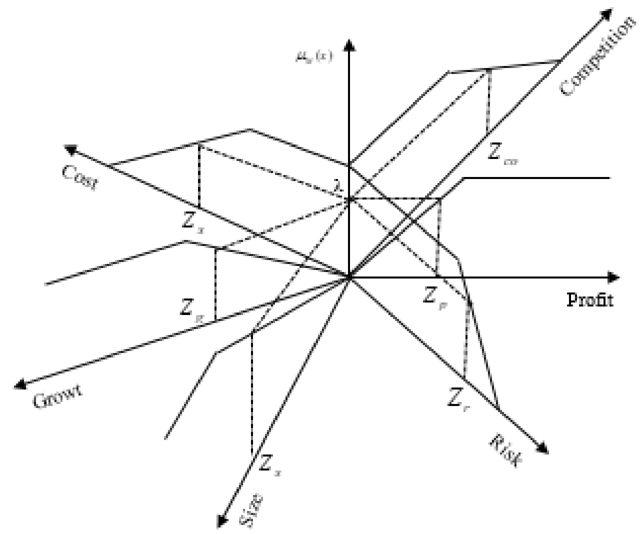


Figure 2. Graphical Fuzzy Multi-Objective Model

Therefore, the whole multi-objective mathematical programming model can be expressed as Equation (5).

$$\mathrm{M}ax \quad \lambda \tag{5}$$

$$
\begin{aligned}
\text{S.T.}\quad & -Z_p + \lambda(U_p - L_p) \le -L_p \\
& -Z_s + \lambda(U_s - L_s) \le -L_s \\
& Z_r + \lambda(U_r - L_r) \le U_r \\
& Z_{co} + \lambda(U_{co} - L_{co}) \le U_{co} \\
& -Z_g + \lambda(U_g - L_g) \le -L_g \\
& Z_c + \lambda(U_c - L_c) \le U_c \\
& Z_p = \sum_{i=1}^{n} p_i x_i \\
& Z_s = \sum_{i=1}^{n} s_i x_i \\
& Z_r = \sum_{i=1}^{n} r_i x_i \\
& Z_{co} = \sum_{i=1}^{n} co_i x_i \\
& Z_g = \sum_{i=1}^{n} g_i x_i \\
& Z_c = \sum_{i=1}^{n} c_i x_i \\
& x_i = 0 \quad or \quad 1
\end{aligned}
$$

Case Implementation

This section illustrates how the market segment portfolio can be determined based on the results of artificial intelligence using the proposed single-objective and multi-objective programming models.

Single-Objective Mathematical Programming

Bringing the data in Table 5 into Equation (1) and assuming S = 500, R = 40, C = 3.5, G = 35, and B = 150, a mathematical programming model of Equation (6) can be obtained.

$$
\begin{aligned}
Max\quad & 56x_1 + 89x_2 + 45x_3 + 93x_4 + 23x_5 + 83x_6 + 50x_7 + 29x_8 + 45x_9 \qquad (6) \\
S.T.\quad & 85x_1 + 61x_2 + 88x_3 + 89x_4 + 90x_5 + 55x_6 + 45x_7 + 87x_8 + 96x_9 \ge 500 \\
& 7x_1 + 6x_2 + 6x_3 + 7x_4 + 6x_5 + 8x_6 + 7_{x_7} + 8x_8 + 3x_9 \le 40 \\
& 0.5x_1 + 0.8x_2 + 0.5x_3 + 0.2x_4 + 0.4x_5 + 0.1x_6 + 0.9_{x_7} + 0.3x_8 + 0.5x_9 \le 3.5 \\
& 5x_1 + 6x_2 + 7x_3 + 6x_4 + 6x_5 + 6x_6 + 7x_7 + 5x_8 + 4x_9 \le 35 \\
& 17x_1 + 22x_2 + 21x_3 + 22x_4 + 24x_5 + 13x_6 + 21x_7 + 17x_8 + 25x_9 \le 150 \\
& x_i = 1 \text{ or } 0,\ \mathrm{I} = 1, 2, \ldots, 9.
\end{aligned}
$$

Using Lingo to solve Equation (6), when $x_1 = x_2 = x_3 = x_4 = x_5 = x_8 = 1$, the maximum overall profit of the firm is 335. Specifically, to achieve this maximum profit, the company should choose the market segments 1 (x_1), 3 (x_2), 5 (x_3), 6 (x_4), 7 (x_5), and 11 (x_8) in Table 5. The details are shown in Table 6.

Table 6

Maximum Profit Combination by Single Objective Model

No	Size	Risk	Competition	Growth	Cost	Profit	Portfolio
1	85	7	0.5	5	17	56	v
3	61	6	0.8	6	22	89	v
5	88	6	0.5	7	21	45	v
6	89	7	0.2	6	22	93	v
7	90	6	0.4	6	24	23	v
11	87	8	0.3	5	17	29	v
Sum	500	40	2.7	35	123	335	
Threshold	≥ 500	≤ 40	≤ 3.5	≥ 35	≤ 150		

To explore in which market segments a company should choose to compete—to maximize the overall profitability under different threshold values—this section changes the threshold values for market size, risk tolerance, competition, market growth rate, and budget, with a view to also understanding the impact on the choice of market segments.

The detailed sensitivity analysis results are shown in Table 7. There are eight simulated cases in Table 7, with Case 1 being the baseline condition, Cases 2 to 6 changing one threshold value at a time, and Case 7 and Case 8 simultaneously changing every threshold value. Then, risk tolerance is scaled up so that all market segments are selected, making it the largest combination of market segments.

Table 7

Sensitivity Analysis of Single Objective Model

Case	Threshold					Profit	Portfolio
	Size	Risk	Competition	Growth	Cost		
1	≥ 500	≤ 40	≤ 3.5	≥ 35	≤ 150	335	1, 3, 5, 6, 7, 11
2	≥ 400	≤ 40	≤ 3.5	≥ 35	≤ 150	405	3, 5, 6, 9, 10, 12
3	≥ 500	≤ 50	≤ 3.5	≥ 35	≤ 150	461	1, 3, 5, 6, 9, 10, 12
4	≥ 500	≤ 40	≤ 4.5	≥ 35	≤ 150	335	1, 3, 5, 6, 7, 11
5	≥ 500	≤ 40	≤ 3.5	≥ 30	≤ 150	357	1, 3, 5, 6, 11, 12
6	≥ 500	≤ 40	≤ 3.5	≥ 35	≤ 250	335	1, 3, 5, 6, 7, 11
7	≥ 400	≤ 50	≤ 4.5	≥ 30	≤ 250	484	1, 3, 5, 6, 7, 9, 10, 12
8	≥ 400	≤ 60	≤ 4.5	≥ 30	≤ 250	513	1, 3, 5, 6, 7, 9, 10, 11, 12

As can be seen from Table 7, the original, baseline Case 1 market segmentations are 1, 3, 5, 6, 7, and 11, and the maximum profit value is 335. When the lower bound of the total market segment sizes is adjusted downward to 400 (as in Case 2), the market segmentations become 3, 5, 6, 9, 10, and 12, and the maximum profit value increases to 405. If the risk tolerance is increased from the base case to 50 for Case 3, the maximum profit value increases further to 461, and the market segment choices become 1, 3, 5, 6, 9, 10, and 12 (i.e., Case 2 plus Market Segment 1). If the competition level is increased from the base case to 4.5 for Case 4, the maximum profit value returns to 335 of the base case, and the market segments are 1, 3, 5, 6, 7 and 11, the same as with the base case. In Case 5, where the total market segment growth is increased to 30 from the base case, the maximum profit value becomes 337–slightly higher than the base case of 355–and the market segmentation is 1, 3, 5, 6, 11, and 12. Case 6 raises the cost upper bound from the base to 250; its maximum profit value is still 335 (as with the base), and the market segmentation is also 1, 3, 5, 6, 7, and 11. The previous cases change one threshold at a time, whereas Case 7 changes all the thresholds simultaneously; the maximum profit value is 484, and the market segmentation is also 1, 3, 5, 6, 7, 9, 10, and 12. Finally, Case 8 relaxes the risk upper bound threshold of Case 7 to 60, where it is found that all market segments (1, 3, 5, 6, 7, 9, 10, 11, and 12) are included in the portfolio, and the maximum profit value is 513.

Looking at Case 2 in Table 7, we can see that lowering the threshold for the aggregate size of the market segments can indeed increase overall corporate profits. In Case 3, we can see that raising the risk tolerance threshold can also increase overall corporate profits, a confirmation of the general perception that high risk comes with high profitability. However, we can see from Case 4 that raising the threshold of the competition does not improve the overall corporate profit; specifically, entering a very competitive market segment is not necessarily helpful for the profits. Case 5 lowers the market segment growth, i.e., taking in some lower growth market segments, and the overall corporate profit changes from 335 to only 337, offering almost no help. Case 6 raises the budget threshold to allow segments from higher-cost markets; it is found that the overall corporate profit is still only 335, indicating that increasing the budget amount may not be the best strategy.

As a whole, if a company does not want to increase its budget, it may be able to obtain good overall profits by slightly increasing its risk tolerance, as seen in Case 3. Another approach follows Case 2: allowing its product to enter relatively smaller market segments; although the profit improvement effect is not as good as Case 3, it is still better than the baseline Case 1. Of course, if a company enters and competes in markets without regard to how risky it is there, it will surely have a chance to increase its profits, but its risk of failure will also be higher, which is the phenomenon and possible results of Case 7 and 8.

Multi-Objective Mathematical Programming

If the data in Table 5 is brought into Equation (5), it can then be expanded into Equation (7) as shown below:

$$
\begin{aligned}
& Max \quad \lambda \qquad\qquad (7)\\
& S.T. -(56x_1+89x_2+45x_3+93x_4+23x_5+83x_6+50x_7+29x_8+45x_9)+(513-335)\lambda \le -335\\
& \quad -(85x_1+61x_2+88x_3+89x_4+90x_5+55x_6+45x_7+87x_8+96x_9)+(611-500)\lambda \le -500\\
& \quad (7x_1+6x_2+6x_3+7x_4+6x_5+8x_6+7x_7+8x_8+3x_9)+(58-40)\lambda \le 58\\
& \quad (0.5x_1+0.8x_2+0.5x_3+0.2x_4+0.4x_5+0.1x_6+0.9x_7+0.3x_8+0.5x_9)+(4.2-2.7)\lambda \le 4.2\\
& \quad -(5x_1+6x_2+7x_3+6x_4+6x_5+6x_6+7x_7+5x_8+4x_9)+(52-35)\lambda \le -35\\
& \quad (17x_1+22x_2+21x_3+22x_4+24x_5+13x_6+21x_7+17x_8+25x_9)+(182-123)\lambda \le 182\\
& \quad x_i = 1 \text{ or } 0,\ i = 1, 2, \ldots, 9.
\end{aligned}
$$

Using Lingo to solve Equation (7), we obtain a value λ of 0.3559322. Except for $X_7 = 0$, the value for X_1 through X_9 is all 1. This means that all the market segments in Table 5 are selected except for market segment 10.

To explore in which market segments a company should choose to compete, this section changes the λ value to understand the impact on the choice of market segments. The detailed sensitivity analysis results are shown in Table

8. There are eight simulated cases in Table 8, with Case 1 being the baseline condition. It is obvious that different λ value leads to different portfolio and the corresponding objective values. When λ is zero, all market segments will be selected, and therefore, the objective values are the highest in all columns. Table 9 compares the results of multi-objective model and single-objective model.

Table 8

Sensitivity Analysis of λ value

λ value	Profit	Size	Risk	Competition	Growth	Cost	Portfolio
0.3559322	463	651	51	3.3	45	161	1, 2, 3, 4, 5, 6, 8, 9
0.35	418	555	48	2.8	41	136	1, 3, 5, 6, 7, 9, 11
0.30	468	608	52	3.7	45	161	1, 3, 6, 7, 9,10, 11, 12
0.25	457	611	51	3.7	47	165	3, 5, 6, 7, 9,10, 11, 12
0.20	457	611	51	3.7	47	165	3, 5, 6, 7, 9,10, 11, 12
0.15	374	590	45	2.5	39	139	1, 5, 6, 7, 9 11, 12
0.10	368	550	45	2.9	41	143	5, 6, 7, 9,10, 11, 12
0.05	374	556	43	3.6	41	152	3, 5, 6, 7, 10, 11, 12
0.00	513	696	58	4.2	52	182	1, 3, 5, 6, 7, 9, 10, 11, 12

Table 9

Comparison of Single and Multi-Objective Models

		Profit	Size	Risk	Competition	Growth	Cost	Portfolio
Multi-objective	Fuzzy method (λ=0.3559322)	463	651	51	3.3	45	161	1, 2, 3, 4, 5, 6, 8, 9
Single-objective	Case 1 (baseline)	335	500	40	2.7	35	103	1, 3, 5, 6, 7, 11
	Case 8 (select all)	513	696	58	4.2	52	182	1, 3, 5, 6, 7, 9, 10, 11, 12

It can be found from Table 9 that, by using multi-objective programming (to select the market segmentation portfolio) and the fuzzy membership function (to approach the extreme value of each objective at the same time), an enterprise can obtain quite good overall profits, market size, and growth, compared to baseline Case 1 in Table 7. The maximum values of the three are 463, 651, and 45, respectively. Of course, the relative risk, degree of competition, and cost are also higher than in Case 1, and the minimum values of the three are 51, 3.3, and 161, respectively. If the enterprise cannot afford the risks, competition, and costs of Case 8, the result of the multi-objective fuzzy programming seems to be an acceptable choice.

Comparison with Scoring Method

It is indicated that scoring method was commonly used for market targeting and prioritization in practice (Wright Associates, 2010), therefore, this section applies the scoring method to solve the same problem in Table 3. The scoring method involves five steps: (1) identify the key factors, (2) specify relative weight to the factors, (3) assign score to each segment against each factor, (4) sum the product of the weight and assigned score, (5) select the market segments portfolio based on the total score and budget (Wright Associates, 2010). Table 10 shows the computation of the scoring method; all data are identical to Table 3 except the relative importance RI_i and the factor weight. The values of RI_i are normalized to become the weight w_i and w_j. Moreover, a plus sign is assigned to the factors that are the higher the better, and minus sign for factors that are the higher the worse. Therefore, the total score of each market segment can be calculated as Equation (8):

$$\text{Total score} = \sum_{i=1}^{m} w_i x_i - \sum_{j=1}^{n} w_j x_j \qquad (8)$$

$$w_i = \frac{RI_i}{\sum_{i=1}^{m} RI_i + \sum_{j=1}^{n} RI_j}$$

$$w_j = \frac{RI_j}{\sum_{i=1}^{m} RI_i + \sum_{j=1}^{n} RI_j}$$

Where w_i is the weight of factor i with plus sign,
w_j is the weight of factor j with minus sign,
x_i is assigned score of factor i,
x_j is assigned score of factor j,
m is the number of factors with plus sign,
n is the number of factors with minus sign.

Take the total score of segment 1 in Table 10 as an example, it is obtained as below:

$$85\left(\frac{1}{6}\right)+5\left(\frac{1}{6}\right)+56\left(\frac{1}{6}\right)-7\left(\frac{1}{6}\right)-0.5\left(\frac{1}{6}\right)-17\left(\frac{1}{6}\right)=28.42$$

For comparison purpose, the same threshold values are applied to the scoring method. The market segments are selected in such a way that high total score has high priority in entering the portfolio, and the selection process is repeated and terminated when threshold values are violated even the budget is not exhausted. Table 10 shows the results when all factors are equally important, and the portfolio is found to be composed of segments 1, 2, 3, 5, 6 and 12. The total market size, total risk, total competition, total growth, total profit and total cost are obtained as 492, 37, 2.9, 31, 404 and 125 respectively.

Table 10

Market Segments Portfolio by Scoring Method

Factor	Size (+)	Risk (-)	Competition (-)	Growth (+)	Profit (+)	Cost (-)	Total score
Relative importance RI_i	1	1	1	1	1	1	
Weight / No	$\frac{RI_1}{\sum RI}=\frac{1}{6}$	$\frac{RI_2}{\sum RI}=\frac{1}{6}$	$\frac{RI_3}{\sum RI}=\frac{1}{6}$	$\frac{RI_4}{\sum RI}=\frac{1}{6}$	$\frac{RI_5}{\sum RI}=\frac{1}{6}$	$\frac{RI_6}{\sum RI}=\frac{1}{6}$	
1*	85	7	0.5	5	56	17	28.42
2*	73	8	0.4	3	76	18	29.73
3*	61	6	0.8	6	89	22	30.80
4	77	9	0.9	3	23	11	20.65
5*	88	6	0.5	7	45	21	27.92
6*	89	7	0.2	6	93	22	36.20
7	90	6	0.4	6	23	24	24.90
8	65	6	0.6	1	48	15	22.60
9	55	8	0.1	6	83	13	27.52
10	45	7	0.9	7	50	21	21.82
11	87	8	0.3	5	29	17	24.38
12*	96	3	0.5	4	45	25	28.92

To explore how the weight affects the selection of portfolio, this section changes the *RI* value to understand the impact on the choice of market segments. The results of five viable cases are shown in Table 11. It can be seen that when threshold values are set as S≧500, R≦40, C≦3.5, G≧35, and B≦150, the market size of Case 2 and Case 3 exceeds 500; the risk of Case 1 and Case 5 is below 40; the competition of all Cases is below 3.5; the growth of Case 2 and Case 3 is above 35. Therefore, if the market size is more important, then Case 2 is better, because it has higher profit than Case 3. If the risk is the major concern, then Case 5 is better than Case 1, because Case 5 has higher profit than Case 1. If the competition is to be avoided, then Case 5 is the best, because it has higher profit than Cases 1, 2, 3, and it also has lower risk than Case 4. If the growth is to be focused, then Case 3 is better, because it has higher profit than Case 2. In summary, Cases 4 and 5 produce the highest profit, and Case 1 the least.

Table 11

Sensitivity Analysis of Weight Values

Case		Size	Risk	Competition	Growth	Profit	Cost	Portfolio
1	*RI*	1	1	1	1	1	1	1, 2, 3, 5, 6, 12
	Total	492	37	2.9	31	404	125	
2	*RI*	4	5	2	3	1	6	1, 2, 3, 5, 6, 7, 12
	Total	582	43	3.3	37	427	149	
3	*RI*	6	5	3	4	1	2	1, 2, 5, 6, 7, 11, 12
	Total	608	45	2.8	36	367	144	
4	*RI*	1	6	5	3	2	4	1, 2, 3, 5, 6, 9
	Total	451	42	2.5	33	442	113	
5	*RI*	2	1	4	3	6	5	1, 2, 3, 6, 9, 12
	Total	459	39	2.5	30	442	117	

Table 12 compares the results by scoring method, multi-objective programming model and single-objective programming model. The Case 2 in Table 11 is used to compare with the results of the programming models, because four factors meet the threshold criteria, namely, the market size 582≧500, the competition 3.3≦3.5, the growth 37≧35, the cost 149≦150. However, the risk of Case 2 is 43, which is higher than the threshold 40, therefore, the risk tolerance is increased to 43 for the two programming models, and all other threshold values remain unchanged. Table 12 lists the results. It is obvious that the portfolio formed by the two programming models not only produces higher total profit, but also generates less total competition, higher total growth and smaller total cost. Besides, the results from the two programming models happen to be identical.

Table 12

Comparison of Results

Approach	Profit	Size	Risk	Competition	Growth	Cost	Portfolio
Scoring method	427	582	43	3.3	37	149	1, 2, 3, 5, 6, 7, 12
Multi-objective (λ=0.2941176)	434	564	43	3.0	40	144	1, 2, 3, 4, 5, 6, 9
Single-objective	434	564	43	3.0	40	144	1, 2, 3, 4, 5, 6, 9

Conclusion

This study proposes a two-stage approach to form a profit maximized market portfolio. The first stage uses three artificial intelligence algorithms to establish a market segmentation performance model and then uses the model to screen new market segments. In the second stage, mathematical programming is used to find a market segmentation portfolio that maximizes profits. Mathematical programming models include the single-objective model and fuzzy multi-objective model. The single-objective model takes the overall profit as the maximum goal, whereas the fuzzy multi-objective model simultaneously maximizes overall profit, market size, and growth and minimizes risks, competition, and cost. Under the same threshold conditions, the maximum profit of the market portfolio found in the single-objective model and the multi-objective model are both higher than that of the conventional scoring method. This research indicates that the artificial intelligence algorithm combined with the two mathematical programming models can indeed find the market segmentation portfolio with better profits in a more scientific way than the scoring method used in practice. Future research can be to use different artificial intelligence algorithm to screen the market segments, and to use other methods to solve the multi-objective programming model, such as genetic algorithm.

References

Almgren, K. (2014). The four factors for targeting an attractive market. *International Journal of Humanities and Social Science*, 4(9), 71–76.

Ascarza, E. (2018). Retention futility: targeting high-risk customers might be ineffective. *Journal of Marketing Research*, LV, 80–98. https://doi.org/10.1509/jmr.16.0163

Asiedu, E. (2016). A atudy of use and impact of market segmentation practices on bank performance: with special reference to commercial banks in Colombia. *Journal of Business & Financial Affairs*, 5, 2–10.

Bergemann, D., & Bonatti, A. (2011). Targeting in advertising markets: implications for offline versus online media. *RAND Journal of Economics*, 42(3), 417–443. https://doi.org/10.1111/j.1756-2171.2011.00143.x

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2019). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48, 1–19. https://doi.org/10.1007/s11747-019-00696-0

Dibb, S., & Simkin, L. (1991). Targeting, segments and positioning. *International Journal of Retail & Distribution Management*, 19(3). https://doi.org/10.1108/09590559110143800

Dominguez, L. V., & Page, A. L. (1984). Formulating a strategic portfolio of profitable retail market segments for commercial banks. *Journal of Economics and Business*, 36(2), 189–206. https://doi.org/10.1016/0148-6195(84)90031-6

Elliott, G., & Glytin, W. J. (1998). A portfolio-based approach to the segmentation of markets for financial services. *Journal of Segmentation in Marketing*, 2(1), 65–83. https://doi.org/10.1300/J142v02n01_05

Gomez-Suarez, M., Quinones, M., & Yague, M. J. (2020). Targeting smart shoppers: a cross-country model. *Journal of Business Economics and Management*, 21(3), 619–705. https://doi.org/10.3846/jbem.2020.11851

Gopalan, R. (2007). Customer portfolio management using Z-ranking of customer segments and the LTV perturbation method. *Journal of Database Marketing and Customer Strategy Management*, 14, 225–235. https://doi.org/10.1057/palgrave.dbm.3250050

Goyat, S. (2011). The basis of market segmentation: a critical review of literature. *European Journal of Business and Management*, 3(9), 45–54.

Gregory, E. G., & Glytin, W. J. (1998). A portfolio-based approach to the segmentation of markets for financial services. *Journal of Segmentation in Marketing*, 2(1), 65–83. https://doi.org/10.1300/J142v02n01_05

Gunay, G., & Gokasar, I. (2021). Market segmentation analysis for airport access mode choice modeling with mixed logit. *Journal of Air Transport Management*, 91. j.jairtraman.2020.102001.https://doi.org/10.1016/j.jairtraman.2020.102001

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49, 30–50. https://doi.org/10.1007/s11747-020-00749-9

Kalam, K. K. (2020). Market segmentation, targeting and positioning strategy adaptation for the global business of vodafone telecommunication company. *International Journal of Research and Innovation in Social Science*, IV(VI), 427–430.

Liu, J., Liao, X., Huang, W., & Liao, X. (2019). Market segmentation: a multiple criteria approach combining preference analysis and segmentation decision. *Omega*, 83, 1–13. https://doi.org/10.1016/j.omega.2018.01.008

Pischedda, L., Manstretta, D., & Diaz, R. M. (2010). Market segmentation and portfolio management - an aanalysis of the Italian ,arket. In 17th Annual European Real Estate Society Conference. ERES: Conference. Milan, Italy.

Power, B. (2017). How Harley-Davidson used artificial intelligence to increase New York sales leads by 2,930 %". Harvard Business Review, May.

Sackmann, S., Kundisch, D., & Ruch, M. (2010). Customer portfolio management in e-commerce: an analytical model for optimization. *Management Research Review*, 33, 617–634. https://doi.org/10.1108/01409171011050226

Smeureanu, I., Ruxanda, G., & Badea, L. M. (2013). Customer segmentation in private banking sector using machine learning techniques. *Journal of Business Economics and Management*, 14(5), 923–939. https://doi.org/10.3846/16111699.2012.749807

Terho, H. (2009). A measure for companies' customer portfolio management. *Journal of Business-to-Business Marketing*, 16(4), 374–411. https://doi.org/10.1080/10517120902762542

Varadarajan, P. R. (1990). Product portfolio analysis and market share objectives: An exposition of certain underlying relationships. *Journal of the Academy of Marketing Science*, 18, 17–29. https://doi.org/10.1007/BF02729759

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights*. https://doi.org/10.1016/j.jjimei.2020.100002

Wright Associates. (2010). Market targeting and prioritization. White paper.

Zanjirdar, M. (2020). Overview of portfolio optimization models. *Advances in mathematical finance & applications*, 5(4), 419–435.

Zhou, H., Norman, R., Kelobonye, K., Xia, J. H., Hughes, B., Nikolova, G., & Falkmer, T. (2020). Market segmentation approach to investigate existing and potential aviation markets. *Transport Policy*, 99, 120–135. https://doi.org/10.1016/j.tranpol.2020.08.018

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