Applying Machine Learning to Luxury Marketing: Utilizing Prediction Model to Develop Brand Strategy

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Abstract. As the luxury market is recovering after the Covid-19 pandemic, luxury companies are utilizing various methods to maintain and expand their customer cohorts. Machine learning prediction model is one effective way to do purchase anticipation and strategy development. Existing studies of machine learning in the business field mainly focus on model construction, while research around luxury marketing is mostly theory-based and lacks model support. Therefore, in this paper, the author constructed the machine learning model and applied the result to luxury brand strategy development. The AO (Aesthetics and Ontology) Framework was used to classify luxury customers into four cohorts. For model construction, the author referred to another machine learning research in the luxury field. Decision tree classification algorithm was used to construct the model as it outperforms other algorithms. As a result, the author uses the prediction results to identify the four customer segments in the AO Framework and formulate luxury marketing strategies respectively. At last, the author points out that a more accurate machine-learning model is needed and there are requirements for data collection, but applying machine learning to the process of luxury marketing strategy development is necessary.

Keywords: Machine learning; luxury marketing; the Aesthetics and Ontology Framework; decision tree; prediction model.

1. Introduction

Regardless of COVID-19's influence on global luxury demand over the past few years, the luxury market is expected to reach an estimation of EUR 360-380 billion by 2025 [1]. Upon recent market analysis, the luxury market is recovering quickly powered by local consumption from top revenue-generating markets and online channels [1,2]. As a result of the big data age, customers' preference shifts and new anticipations towards products and brands after the pandemic are not only reflected by word of mouth, but also by the data collected from the purchasing system. Under this circumstance, how to process data to target the effective customer group, make production decisions and formulate luxury marketing strategy has become a key to the success of a luxury brand in the post-pandemic era. To make the best of the existing data, machine learning is an outstanding method for building prediction models. Research papers about building machine learning models in the business world are numerous, such as using deep learning networks to predict stock market, applying principal component analysis (PCA) to assist company questionnaire, utilizing latent semantic analysis (LSA), bidirectional encoder representations from transformers (BERT) and support vector machines (SVM) to facilitate human resource management and so on [3-5]. These papers discuss the mathematical principles and technical methods in detail, showing machine learning's feature of non-human intervention and high capability of handling multi-dimensional and multi-variety data [6]. In the luxury marketing field, academic articles are combinations of theoretical analysis and case studies including methodologies like interviews and document analysis. For example, the research study carried out by Liz Thach et al. used a qualitative methodology of interviewing along with analysis of website and marketing materials to look into the luxury wine market in the case of Burgundian wineries [7]. Some luxury marketing papers would involve a certain degree of data analysis, but the majority of them are basic statistical calculations or empirical experiments based on observation, such as calculating the probability of usage of one product under the influence of free samples and exclusive distribution to understand the experiential luxury marketing strategy [8]. In general, research papers around business machine learning models focus on the accuracy of model

construction and data output but lack discussion about the following brand development and marketing strategy, while research about luxury marketing lacks data and modeling support, making it difficult to produce convincing luxury marketing tactics.

In this paper, the machine learning prediction model and luxury marketing strategy will be combined. Firstly, the author discusses a framework of luxury brand typology and customer type. Secondly, a machine learning prediction model based on purchasing habits and characteristics data of luxury goods will be introduced. At last, how to use the machine learning results to formulate marketing strategy in accordance with the luxury brand typology will be presented.

2. Method

2.1. Luxury Customer Segmentation – The AO (Aesthetics and Ontology) Framework

In this section, the AO Framework (Figure 1) came up by Pierre Berthon et al. will be discussed [9]. According to them, based on Alfred North Whitehead's process philosophy and Martin Heidegger's theory of art, luxury brands can be classified into four categories by using two measures: aesthetic and ontology [9-11]. In essence, different luxury brand positions are referring to different customer segmentations' interests. Therefore, the framework used for luxury brand classification is also applicable to luxury customer segmentation. Here the AO Framework will mainly be used to look at luxury customer cohorts.

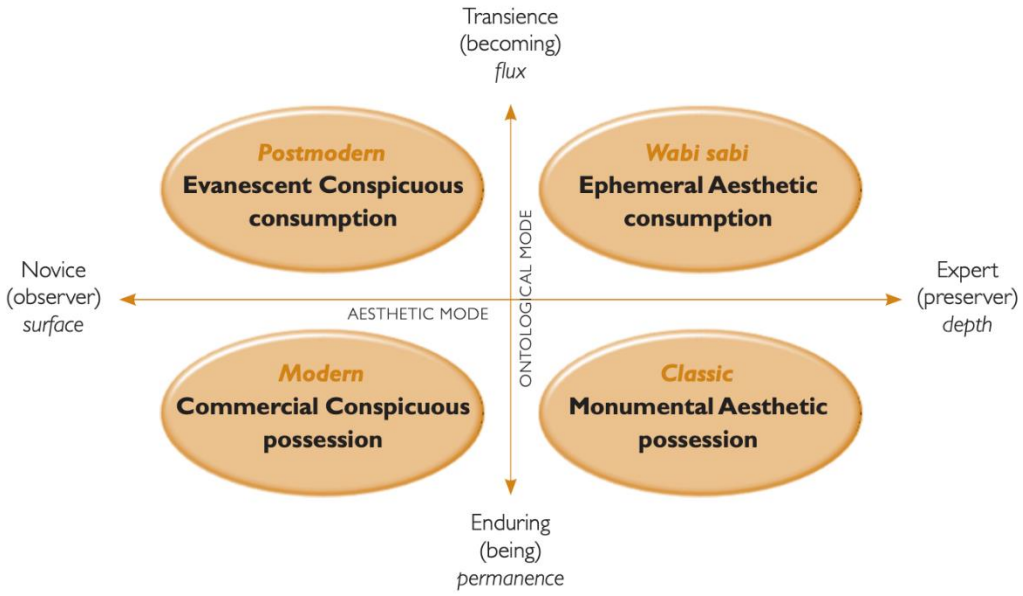


Fig 1. The AO Framework

2.1.1 Overview of AO Framework

The measurement aesthetic assesses whether one can discriminate the value or artisanship in the object. As Heidegger stated, the ending of the physical work does not stand for the completion of a piece of art [12]. This argument remains true for luxury products. Despite the numerous variations of the definitions of luxury, one feature stays constant: an exclusive and excellent experience throughout the whole process from product development to after-sales [9]. Luxury is a process, instead of a thing [9]. As a result, the knowledge and experience the owner gained from the luxury product take on a crucial position. The word "preserver" was used by Heidegger to describe one who completes the artwork by experiencing it immersively, which could also be used on those who fully appreciate and experience the luxury; the other end is called "observer" [10]. Intuitively, preservers are consumers used to purchasing and enjoying luxury products, and observers are those who were not exposed to luxury before and are new to the products. The term ontology is the subfield of metaphysics, which studies the nature of reality or being. Reality, according to certain philosophers can either be

permanence or flux, being or becoming [9]. Applying this philosophical idea to luxury and its customers, endurance and transience are associated. The endurance of luxury refers to the items that can last, such as diamond and antique artworks. Transience means luxury products or services that only happen in a limited period of time, such as the experience in a luxury restaurant. A typology of luxury brands and customers can be provided by taking these two dimensions together.

2.1.2 The Modern

In this segment, enduring and novice is the main feature. The modern customers have limited expertise to appreciate luxury and pursue products that last long. The admission criterion for modern customers is money. They purchase luxury products mainly to show their exclusive social status, thus what they long for is commercial conspicuous possession. Common purchasing items include cosmetics, entry-level accessories and ready-to-wear.

2.1.3 The Classic

Consumers in the classic quadrant want enduring and expert luxury products. They consider luxury as commemorative art. They have the expertise to fully appreciate and experience the luxury product or service, so their intention is to seek monumental aesthetic possession. What classic buyers usually purchase include artworks, fine watches, yachts, shotguns and so on. This segment has a high barrier as it requires professional knowledge rather than just money in order to enjoy the luxury [9].

2.1.4 The Postmodern

This type of customer stresses transience and novice. They have enough money to buy luxury goods, but do not know how to appreciate them. They have a preference for showing off, so they choose to consume in front of the public and purchase frequently. Postmodern customers mainly care about appearance and surface, so examples of postmodern luxury products include designer evening dresses that are worn only once, obvious facelifts, makeovers and so on [9]. Here luxury, as shown in Figure 1, is evanescent conspicuous consumption.

2.1.5 The Wabi Sabi

This quadrant emphasizes transience and expertise. Here luxury is a deep taste of the current moment; it is mindfulness of ephemerality [9, 13]. Wabi Sabi customers' purpose is to seek present pleasure. For example, Wabi Sabi customers will open first-growth Bordeaux wine whenever they want to enjoy it, while others may save it for special occasions for celebration. For them, what matters is the aesthetic experience of luxury, not the possession. They want ephemeral aesthetic consumption. Luxuries such as high-end restaurants with excellent taste and service are attractive to them.

2.2. Machine Learning Classification Algorithm Selection and Model Construction

This section is a description and extension of the research carried out by Qiaoshan Chen et al., who constructed a machine-learning model to predict luxury customers' future purchases [14]. The researchers build a prediction model by using decision tree to analyze the historical data. They forecast each customer's purchase demand and evaluate the possibility of purchase variation, including three categories of cosmetics, jewelry and clothing. This is an example of product classification. If applied to practical business analysis, the classification can be more refined.

2.2.1 Classification Algorithm Selection – Decision Tree

The decision tree is a common classification algorithm. As shown in Figure 2, the entire dataset is represented as a tree by the decision tree algorithm, and the classification problem is roughly transformed into choosing the route from top to bottom, which is referred to as root and leaf, depending on different conditions at each level of the decision tree [15]. Root nodes, branches, internal nodes and leaf nodes are components of a decision tree. Each decision node represents a feature in the data set. The goal of it is to create an algorithm with a high capacity for generalization [16]. Decision tree algorithm has the advantage of easy understanding and strong data analysis capability, but it also has the problem of overfitting.

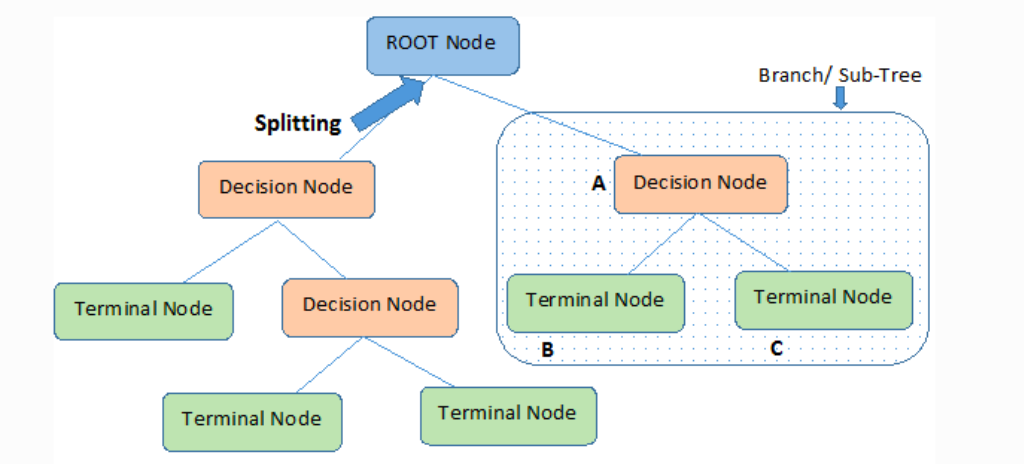


Fig 2. Structure of Decision Tree Algorithm

Table 1. Empirical results of all classification algorithms

Algorithm	Accuracy	Error	Precision (positive)	Recall (positive)	Precision (negative)	Recall (negative)	F1 measure
ANN	0.926	0.071	0.148	0.562	0.990	0.934	0.475
Decision tree	0.930	0.072	0.156	0.598	0.992	0.934	0.501
KNN	0.968	0.033	0.322	0.349	0.968	0.910	0.665
Logistic regression	0.927	0.071	0.689	0.003	0.927	1.001	0.008
SVM	0.922	0.779	0.198	0.443	0.979	0.941	0.550

Table 2. Evaluation parameters of all classification algorithms

Algorithm	Calculation speed (s)	Classifier's fitness for data	Interpretability	AUC value
ANN	266.71	Data do not need to be standardized	Complex	0.597
Decision tree	206.81	Data need to be standardized	Strong	0.611
KNN	210.34	Data need to be standardized	Not strong	0.598
Logistic regression	187.79	Data need to be standardized	Strong	0.525
SVM	375.69	Data need to be standardized	Complex	0.605

Here the researchers chose to use decision tree as the machine learning algorithm for classification because it performs relatively better than other candidates, which are artificial neural network, K-nearest neighbor (KNN), logistic regression and support vector machine. The researchers divided the sample set into two sections to construct a model to find the optimal algorithm, which is the training set and testing set. The result of the analysis of all algorithms is displayed in Table 1. Table 2 shows other evaluation parameters including AUC value. Based on the testing result and the advantage mentioned in the previous context, the researchers choose decision tree as the classification algorithm.

	CTT_DESC	GND_MEMD	age	PUR_CST_ID	FREQ	TLL_FREQ	TTL_SPENDING	QTY	N_PROD	Fragranoe_sales	Make_Up_sales	Skin_Care_sales
1	Normal middle	Female	43	155150	1	3	2125.00	3	3	NULL	1400.00	725.00
2	Vip	Female	44	4579	2	3	148.00	3	3	NULL	670.00	810.00
3	Normal middle	Female	41	68685	1	2	1780.00	4	2	NULL	640.00	1140.00
4	Top Vip	Female	NULL	44170	7	18	25340.00	20	16	1240.00	2190.00	21910.00
5	Normal middle	Unknown	NULL	44253	1	4	2310.00	5	4	NULL	1890.00	420.00
6	Valuable middle	Female	49	59980	1	3	1505.00	3	3	NULL	1000.00	505.00
7	Top Vip	Female	34	25935	5	12	6925.00	13	12	3415.00	3510.00	NULL
8	Normal middle	Female	45	82659	1	1	320.00	1	1	NULL	320.00	NULL
9	Normal middle	Female	38	82791	1	1	600.00	1	1	NULL	600.00	NULL
10	Vip	Female	37	52526	1	1	350.00	1	1	NULL	350.00	NULL
11	Valuable middle	Female	NULL	62303	2	5	2860.00	5	4	690.00	2170.00	NULL
12	Vip	Female	34	83861	4	8	5960.00	8	8	NULL	2540.00	3420.00
13	Vip	Female	56	83910	4	5	1615.00	5	5	365.00	1250.00	NULL
14	Normal middle	Female	29	77060	1	1	320.00	1	1	NULL	320.00	NULL
15	Normal middle	Female	37	18081	1	1	1520.00	1	1	1520.00	NULL	NULL
16	Inactive	Female	53	83976	1	1	365.00	1	1	365.00	NULL	NULL

Fig 3. Model variables arrangement

2.2.2 Construction of Machine Learning Model

Here the researchers collect purchase data on luxury commodities and build a prediction model of purchasing needs. The data is from July 1, 2017 to March 31, 2018. Three tables – cosmetics, jewelry and clothing – are created after classifying the variables required for modeling by processing the raw data. Data preparation and cleaning is the first step. The original database contains 16 variables. Figure 3 displays the variables arrangement. The researchers sort out the data for modeling by calculating the consumption and quantity ratio of three categories. After that, SPSS software was used to mark two kinds of data as NULL: values beyond three standard deviations and people outside the age range 18-60. The researchers applied the linear interpolation technique to deal with the missing values, specifically in age and gender columns. Data standardization is also necessary since many algorithms are involved and the following normalized conversion function is used:

$$y_{ik} = \frac{x_{ik} - \min(x_k)}{\max(x_k) - \min(x_k)} \quad (1)$$

Table 3. Descriptive statistics of numerical variables

	N	Minimum	Maximum	Average	Standard deviation
AGE	294345	18	60	31.36	7.520
FREQ	294345	1	94	1.62	2.049
TTL_SPENDING	294345	-7346	172926	2341.95	4169.208
QTY	294345	-9	230	3.55	5.443
Effective	294345	--	--	--	--

Table 4. Frequency statistic result of customer level

	Customer level	Frequency	Percentage	Effective percentage	Accumulated percentage
Effective	0	20	0.0	0.0	0.0
	1	114002	38.7	38.7	38.7
	2	139450	47.4	47.4	86.1
	3	40872	13.9	13.9	100.0
	Total	294345	100.0	100.0	--

Before modeling, researchers carried out a descriptive statistical analysis. Table 3 shows the detailed statistical analysis of numerical variables, including age, frequency, total spending and total quantity. For detailed statistical analysis of classified variables, Table 4 shows the frequency statistic result of customer level—a higher customer level means higher customer value.The next step is to construct the model and decision tree is the selected algorithm for modeling. The total amount of data is 294,345 and they are classified into three tables. Although the model's precision is excellent, its F1 measure, recall rates, and prediction accuracy are all below expected. The prediction results are set out in Figure 4. 0 means the potential purchase and 1 means the unattainable purchase. It can be seen that the stability of the prediction is high. In addition, the AUC value of three tables are high, 0.967, 0.821 and 0.855 respectively, representing a high accuracy.

3. Discussion -- Using Machine Learning Results to Formulate Brand Strategy

In the constructed machine learning model, some characteristics of the prediction results are able to show in which quadrant of the AO Framework each customer locates, thus enlightening the main customer segmentation of the luxury brand. In the following context, the model prediction results corresponding to the four customer segments and their respective marketing strategy analysis will be provided. Figure 5 shows the corresponding strategies for luxury brand development.

	pur_cst_id	0	1
1	3224348	0.96747967	0.03252033
2	3224373	0.96747967	0.03252033
3	3224380	0.96747967	0.03252033
4	3249469	0.96747967	0.03252033
5	3272986	0.96747967	0.03252033
6	3272999	0.96747967	0.03252033
7	3273001	0.96747967	0.03252033
8	3273018	0.96747967	0.03252033
9	3273035	0.24038462	0.75961538
10	3273050	0.96747967	0.03252033

(a)

	pur_cst_id	0	1
1	3029250	0.96747967	0.03252033
2	3223716	0.96747962	0.75961538
3	3223731	0.96747967	0.03252033
4	3223733	0.96747967	0.03252033
5	3223750	0.96747967	0.03252033
6	1963347	0.96747967	0.03252033
7	3030005	0.96747967	0.03252033
8	3030082	0.96747967	0.03252033
9	3224337	0.24038467	0.03252033
10	3224339	0.96747967	0.03252033

(b)

	pur_cst_id	0	1
1	3256718	0.96747967	0.03252033
2	3256743	0.96747967	0.03252033
3	3256745	0.96747967	0.03252033
4	3256777	0.96747967	0.03252033
5	3163821	0.74431818	0.25568182
6	3163832	0.74431818	0.25568182
7	3163896	0.96747967	0.03252033
8	3163998	0.96747967	0.03252033
9	3164023	0.24038467	0.03252033
10	3164030	0.74431818	0.25568182

(c)

Fig 4. Model prediction results of (a) jewelry, (b) cosmetic and (c) clothing

3.1. The Modern -- Exclusivize

The modern customers' goal of purchasing luxury products is to show their exclusive social status while keeping the cost to a minimum. Therefore, in the machine learning model results, customers predicted to have higher total spending and purchasing quantity in cosmetics, entry-level accessories

and ready-to-wear are most likely to be the modern customer segment. To maintain and gain these customers, the best strategy is to exclusivize the brand. The company can avoid the dilution of brand value by controlling the price and production scale. Selling through brand stores is the best distribution method, and a limitation should be put on licensing to third-party distribution. Location for offline stores needs careful selection to highlight the distinguishment from common brands. The key to exclusivizing is to make it scarce.

3.2. The Classic -- Educate

In this customer segment, the expertise to fully appreciate luxury is the main feature. Thus, from the result of the machine learning model, if the customer has higher spending and purchasing quantity in high-end products with cultural history or requiring professional skills, and possibly has an older age, he might be a classic buyer. For this customer segment, consumer education is the goal of the brand strategy. In order for the target customer cohort to comprehend and value what makes the offering speical and valuable, they must be educated on its intricacies. [9]. A successful example in history was California winemaker Robert Mondavi. In the 1970s, most Americans associate wine with goner, but Mondavi promotes the idea that wine is part of the lifestyle and can be paired with master dishes to enjoy. He held concerts and wine parties in his factory, also collaborating with classic high-class French wine brands to promote their own product [9]. Therefore, the key of marketing to classic buyers is to convey the embedded product story or the intangible concept to them, educating them about the specialty.

3.3. The Postmodern -- Popularize

Postmodern customers like conspicuous purchases to show off. If the prediction result shows a relatively high purchasing frequency and purchasing time happens around the launch of special products or special marketing events, these customers tend to be postmodern customers. The strategy to attract this kind of customer is to popularize the brand. One big characteristic of postmodern customers is that they like to post their possession or experience on social media after purchasing. They care much about their digital presence and follow popular trends online. Influencer marketing can be an effective way to expand the postmodern customer cohort. Brands can collaborate with influential bloggers to promote luxury products to reach out to potential postmodern customers and create trends or keywords like “must have.” Curating Instagram-worthy offline marketing events such as pop-up stores is also one way to gather them. In general, developing marketing strategies around the idea of presentable products or experiences is what draws postmodern customers.

3.4. The Wabi Sabi -- Expertize

For Wabi-sabi customers, seeking pleasure experience in the current moment is the main purpose of purchasing luxury products. In the machine learning prediction results, if the customer has higher spending on products or services with good experience and has a special interest in some neglected products, he is likely to be in the wabi-sabi segment. For them, the recommended strategy is to expertize. The marketing manager needs to create products and services that can encourage and motivate customers to enjoy the moment, to experience because they want to experience, and to learn because they are curious about the knowledge [9]. One example can be some institutions of higher education. A master's degree in Liberal Arts focusing on the topic of what to do in the next stage of your life was offered at the University of Chicago. This program is multidisciplinary, containing courses from humanities, social science and natural science [9]. It is taught by top professors in the university. This program is not aimed at providing students with qualifications to enter a specific industry, but rather to give them the joy in the experience of learning and exploring their future. For wabi-sabi customers, the traditional meaning and purpose of the luxury product is not important, what matters is what experience or value the product itself can bring to them, so to expertize the product is the key strategy.

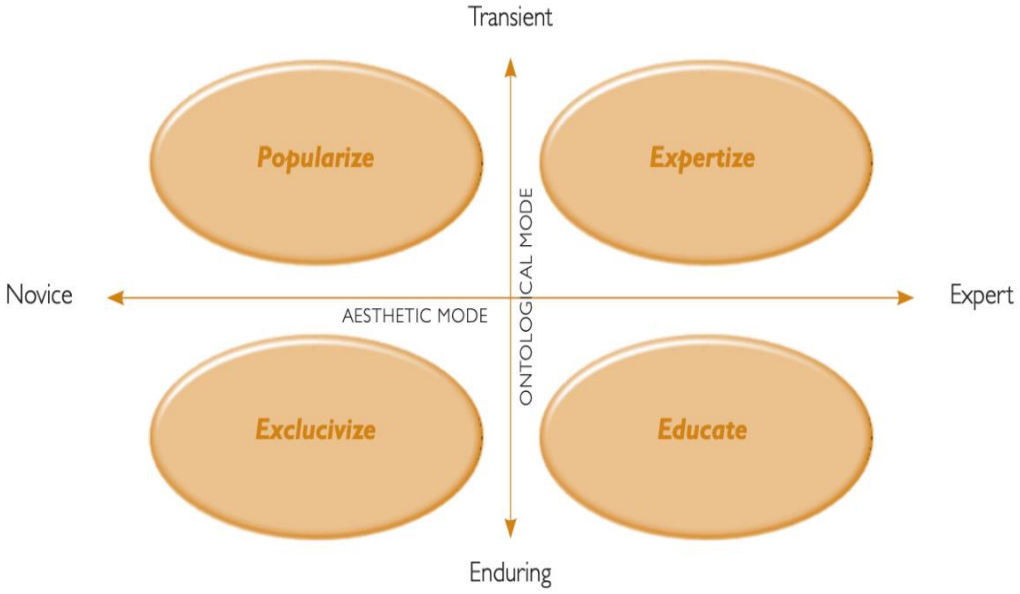


Fig 5. The AO Framework and corresponding strategy

4. Conclusion

This paper discusses how to apply the machine learning prediction model to practical luxury marketing strategy development. At first, the Aesthetics and Ontology (AO) Framework is introduced to do the luxury customer segmentation and their features are explained. After that, a machine learning prediction model based on purchasing habits and characteristics data of luxury goods is discussed. At last, the author used the machine learning results to formulate luxury marketing strategies based on the AO Framework. In the construction of machine learning prediction model, the data sample is collected before the Covid-19 pandemic, but in practice, only data after the pandemic should be used, because customers' purchasing habits have changed after the pandemic and mixing the data might provide inaccurate outcome. Also, the classification of luxury products can be refined. Instead of having only tables of cosmetics, jewelry and clothes, more categories, such as entry-level, high-end, limited edition and so on, can be created for the sake of the following result analysis and customer segmentation. Moreover, the age range of the data can be expanded. The current age range is 18-60, while many classic customers are older than 60 and modern/postmodern customers are teenagers younger than 18. This paper's main contribution is to closely combine machine learning with luxury marketing, providing modeling and data support for luxury marketing strategy development. The brand strategy can be more effective and credible with the backup of a machine learning prediction model. For further research, a more accurate model would be the future direction. As mentioned before, the existing model is already accurate, but still needs to be improved. In general, applying machine learning to the luxury marketing process is necessary for accurate and effective strategy development.

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