Identifying Shopping Centers with High Operating Loss Risk and Potential Redevelopment Opportunities in an Overbuilt Market

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Abstract

In an overbuilt market, commercial real estates face higher loss risks because of intensive competition, which is not conducive to create long-term value. Finding out commercial real estate with high operating loss risk help the developers and government learn the market facts and make rationale investment or redevelopment decisions. Taking shopping center in Shanghai as the research objects, this project try to create a model to estimate operating loss risk based on Huff model and real estate finance formulas. 57 out of 392 shopping centers are identified with high loss risk.The results are tested with social media data with 0.86 accuracy. We also quantify the location value using entropy weight method (EWM) and analyze the mismatch of operation and location value with regression model. 7 outliers are identified with high location value but low operation performance, which can be considered to redevelop.

Keywords: Shopping center, Operation risk, Overbuilding

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1 Introduction

Overbuilding is an urban issue that real estate supply beyond local demand. From a macro scope, overbuilding bring negative economic and social impacts. Dong (n.d.) analyzes the behavior of local government and real estate development and believes real estate over-development does harm to social welfare and ring series of investment risks. Li et al. (2018) stated that over development has an inhibitory effect on private investment through vampire effect, raising costs and reducing demand effect. From the micro scope, studies and media reports noted the operation risk in an over-supply market (Zhang (2013); Yun (2021); Yingshang.com (2020)). Therefore, risk assessment is a vital topic in a overbuilt market. The key risks factors includes location of the property, tenant demand, solvency of tenants, lease maturities, vacancy, renovations, cash flows (especially rents and CAPEX), financing, liquidity and etc (Kohonen et al. (2015)). This research focused on the risk of cash flow, using net operation income (NOI) as a metric. NOI represents a property's gross operating income, minus its operating expenses.It's a key metric to measure the performance and value of commercial real estates. In ISO 31000, risk assessment includes three sub-processes: risk identification, risk analysis and risk evaluation. We focuses on the process of risk identification, which is used to find, recognize, and describe the risks that could affect the achievement of objectives.
Traditionally, operating loss risk is evaluated using the real cash flow numbers. A asset faces operating loss when its NOI is negative, which is not conducive to create long-term value. However, the NOI of each shopping center is usually not exposed to the public. There is information gap between the asset owner and other players. To solve this problem, this research created a model to identify shopping centers with high operating loss risk using open data sets. The structure of model is based on Huff model and real estate finance formulas. Besides, to find out overbuilt shopping centers with redevelopment potential, I analyzed mismatch of operation and location value with entropy weight method and regression model.

2 Background

2.1 Oversupplied commercial real easte market with climbing vacancy rate

At present, number of shopping centers opened or to be opened in Shanghai will be as high as 419. For 2020, The area of shopping centers per person is 0.97 m^2. Both count and area of malls are dramatically increasing since 2009.(Figure 1.). Vacancy rate is an indicator of market cycle. High vacancy rate means the supply is beyond demand. From (Figure 2.)., the vacancy rate in Shanghai is climbing since the third quarter of 2019.

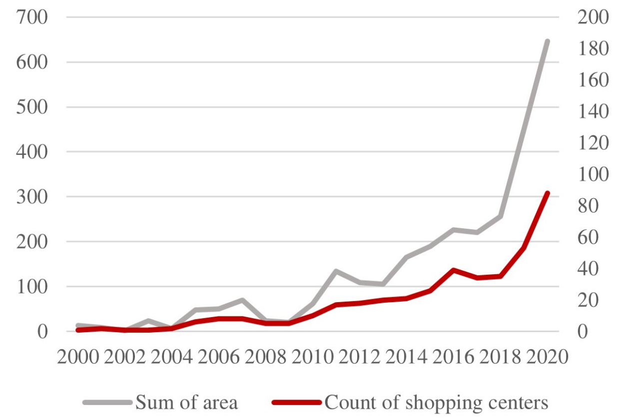

Figure 1: Number of shopping centers 2009-2020

Figure 2: Vacancy rate 2019 Q1-2021 Q1

2.2 Real estate industry in China: from incremental era to stock operation era

In order to promote the healthy development of the real estate marketChinese government now are take series policies including limiting land auction, increasing mortagage rate of developers, property taxes and etc. Many experts make a judgment that real estate industry in China are transforming from incremental era to stock operation era. Jian Sheng (2020) from Oliver Wyman proposed that commercial real estates are facing the challenge of oversupply, insufficient management skills and the pandemic. Only with good asset management skills, could a shopping center survive in intensive competition. In this background, operating loss risk is an essential indicator for the evaluation of the management performance.

2.3 Application of Huff model in retail business

Huff model is an established theory in spatial analysis. It is based on the principle that the probability of a given consumer visiting and purchasing at a given site is a function of the distance to that site, its attractiveness, and the distance and attractiveness of competing sites. It's widely use in the retail industry to estimate customers' patronization. Kim et al. (2011) and Su and Youn (2011) applied huff model to estimate retail market in South Korea and China. Suárez-Vega, Gutiérrez-Acuna and Rodríguez-Díaz (2015) utilized Huff model to locate supermarket.

In this research, Huff model plays an important part of the estimation model. It's applied to predict the number of customers for each shopping center.

3 Data

3.1 Data resources

The input data includes data of shopping centers, social economics data and urban environment data.Information of shopping centers is wrangled from Yingshang.com in Jan. 2022, including the name, building area and building year of each shopping center. Yingshang.com is a website focuses on the commercial real estate and keeps updating information og shopping center projects located in major cities in China. The raw data set contains 429 shopping centers. After cleaning the shopping centers with incompleted information and closed ones, 392 shopping centers remained.Socioeconomics data is downloaded from Chinese statistical year book (2020), the latest edition at present, which includes population, disposable income and consumption expense of each neighborhood.Urban environment data is purchased from third party, which contains geometry data of roads, parks, subway stations and other POIs. The social media data is used to validate accuracy, including average consumption and number of comments of each shopping center. Dianping is a platform for reviewing local venues such as restaurants, shopping, hotels, much like Yelp in the United States. Since Dianping has set a strict Anti-reptile mechanism, the data is manually collected.
To test the preditctive capability All input data is historical data before 2020 Social media data used to test accuracy is up to date.

Categories	Resources	Columns	Type
Shopping centers	Wrangled from Yingshang.com	building_area	float
		rentable_area	float
		built_year	integer
	Baidu Map API	coordinate	geometry
Socioeconomics	Chinese statistical year book (2020)	population	integer
		population density	float
		disposable_income	integer
		consumption expense	integer
Urban environment	Purchased from third party	roads	geometry
		parks	geometry
		subway_stations	geometry
		POIs	geometry
		university_cities	geometry
Social Media	Dianping.com (March,2022)	number of comments	integer
		average consumption	integer

Table 1: Data resources

3.2 Data exploration

Shopping centers are unevenly distributed in Shanghai. A great number of shopping centers cluster in the city center and secondary centers (Figure 3.). The situation is similar seeing from the area of shopping centers per capica. The unevenly distributed pattern leads to residents living in Songjiang District and Chongming Town with low accessibity to the malls, while the competition in the downtown is intensive.
Consumption capacity is is the product of population and consumption. From the perspective of population density, population in Shanghai is highly clustered at the city center (Figure 5.). Neighborhoods with high consumption capacity are large-size suburban communities, where middle class gathers. (Figure 6.).

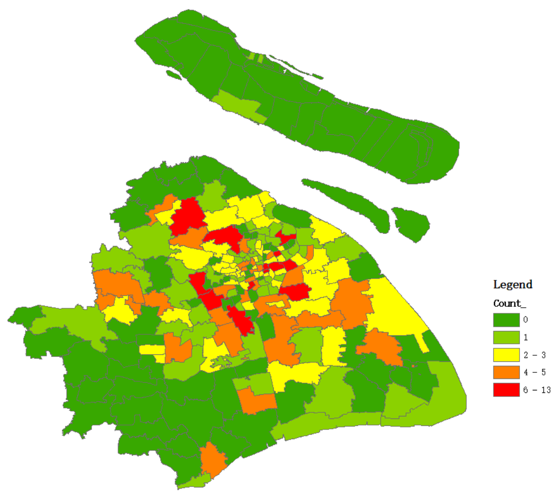

Figure 3: Count of shopping centers by neighborhood

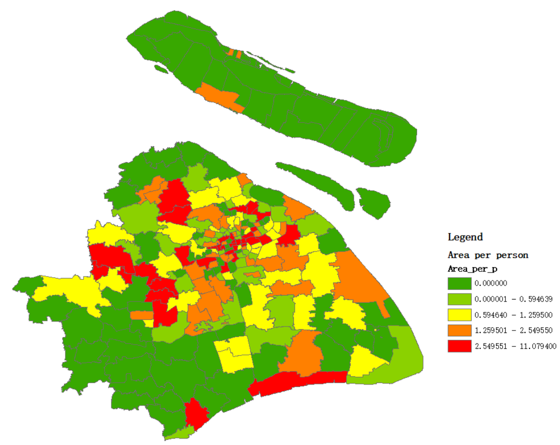

Figure 4: Area of shopping centers per capica

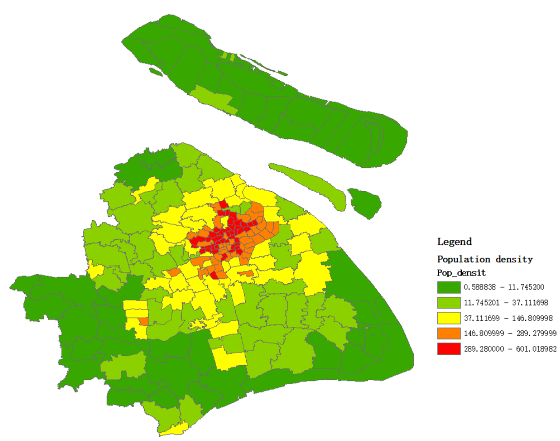

Figure 5: Population density by neighborhood

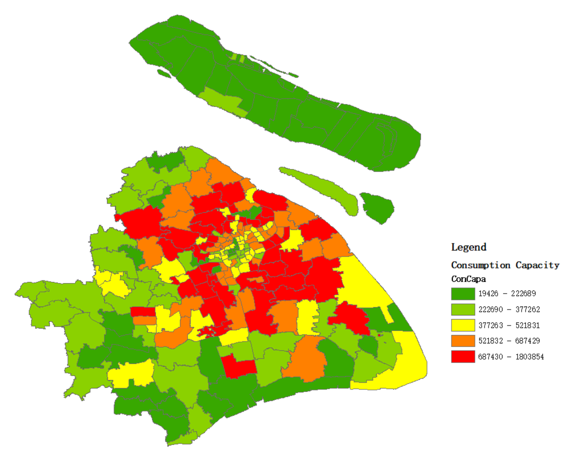

Figure 6: Consumption capacity by neighborhood

Urban environmental data is utilized to quantify the location value of each shopping center. The raw data of road networks with high accuracy of branch road. This research filter only major and secondary road for simplicity. The subway station data is updated to 2021. The No.14 line opened in Dec. 2022 are not included (Figure 7.).

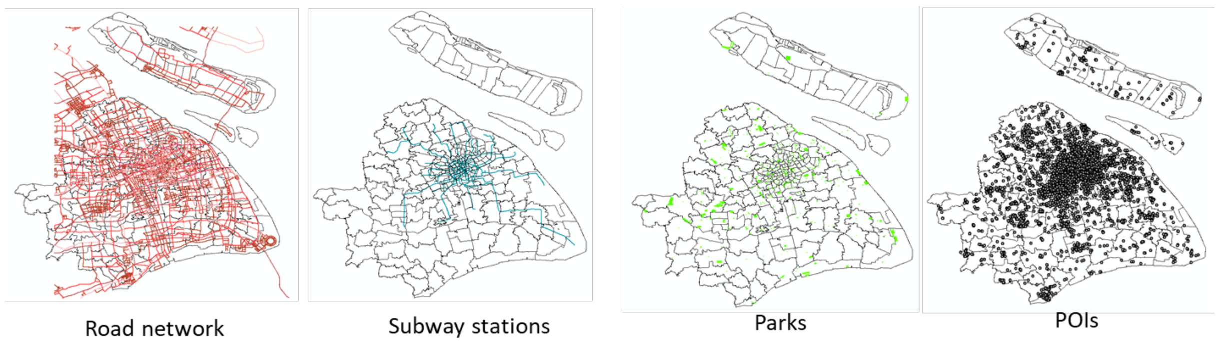

Figure 7: Urban environmental data

Seeing from the social media data, Almost half of the shopping centers received comments within 1000. In most shopping mall, customers spend an average of 100 to 300 yuan .

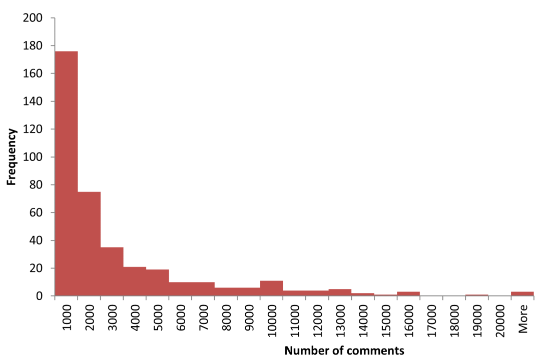

Figure 8: Frequency of number of comments

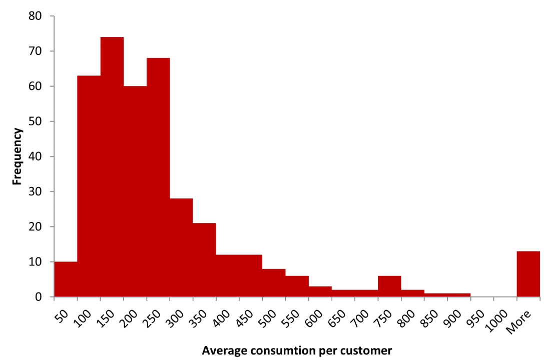

Figure 9: Frequency of average consumption in shopping center

4 Methodology

4.1 Identifying shopping centers with high operating loss risks

Step 1: Applying Huff model to estimate number of customers of each shopping mall

For the first step, I applied Huff model to calculate a matrix of customer share from each neighborhood and for each target shopping center. The form of Huff model is:

$$P_{ij} = \frac{W_i / D_{ij}^{\alpha}}{\sum_{i=1}^{n} \left(W_i / D_{ij}^{\alpha} \right)}$$

where

- P_{ij}=the probability of consumer j shopping at store i.
- W_i=a measure of the attractiveness of each store or site i.
- D_{ij}=the distance from consumer j to store or site i.
- α=an exponent applied to distance so the probability of distant sites is dampened. It usually ranges between 1.5 and 2.

In my model, j is the centroid of neighborhood and i is the location of shopping center. Area of each shopping center was input as W_i, which represents attractiveness of each store. I tried two methods to calculate D_{ij}. The first version calculated the straight line distance, while the second version calculated the real distance using on the road network. Then, I compared the accuracy of two models in the following steps.

Figure 10: Pipline of Step 1

Below is a subset of probability results.Each column represent each neighborhood, and row index is the serial number of each shopping center.

	1	10	100	101	102	104	105	106	107	108	...	93	94	95	96	97
0	0.001741	0.000152	0.000580	0.001578	0.004740	0.003061	0.000196	0.001601	0.015114	0.006493	...	0.000623	0.005329	0.003351	0.002660	0.002303
1	0.001761	0.000157	0.000597	0.001542	0.004887	0.003114	0.000203	0.001729	0.010063	0.006131	...	0.000623	0.005482	0.003378	0.002697	0.002285
2	0.001002	0.000065	0.000298	0.002049	0.002515	0.001983	0.000095	0.000426	0.000705	0.029481	...	0.000518	0.002707	0.002420	0.001757	0.002317
3	0.001527	0.000129	0.000496	0.001464	0.004037	0.002662	0.000166	0.001272	0.026363	0.006388	...	0.000557	0.004555	0.002957	0.002327	0.002085
4	0.001128	0.000089	0.000367	0.001402	0.003102	0.002153	0.000125	0.000774	0.015585	0.007256	...	0.000483	0.003354	0.002479	0.001908	0.001869
5	0.001081	0.000068	0.000315	0.003505	0.002893	0.002159	0.000113	0.000421	0.000518	0.055122	...	0.000727	0.002863	0.003234	0.002280	0.002715
6	0.000562	0.000046	0.000192	0.000641	0.001636	0.001085	0.000067	0.000448	0.202322	0.002845	...	0.000237	0.001756	0.001244	0.000972	0.000874
7	0.000541	0.000039	0.000173	0.000755	0.001462	0.001055	0.000057	0.000314	0.001833	0.004872	...	0.000241	0.001579	0.001206	0.000913	0.000997
8	0.001935	0.000135	0.000574	0.002055	0.004850	0.003710	0.000179	0.000922	0.001823	0.022705	...	0.000773	0.005226	0.003800	0.002817	0.004014
9	0.001616	0.000146	0.000554	0.001371	0.004534	0.002858	0.000189	0.001669	0.004567	0.005319	...	0.000564	0.005094	0.003076	0.002467	0.002057

Figure 11: Results of gravity model (See appendix for full version)

Step2: Calculating annual cost and income using real estate financial formulas

With the number of customers calculated by the gravity model, real estate financial formulas was used to calculate NOI, which is annual Net Operation Income of each shopping center. If NOI is below 0, it means the shopping center is losing moeny based on our prediction result. Then, it was labeled with high operating loss risk. Otherwise, it's classified as low operating risk. The number of identified malls with high risk is recorded as X. The assumption number referenced the market report of commercial real estates in China (Wei (2021)).

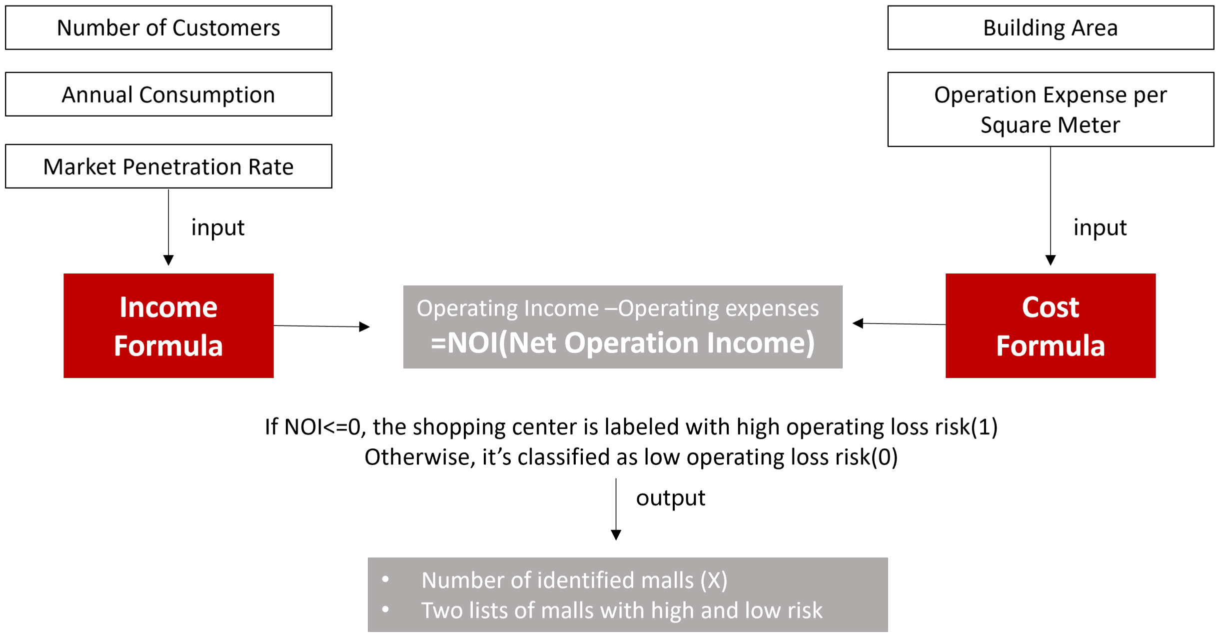

Figure 12: Pipline of Step 2

Below are equations to calculate operation income and operation expense:

$$\text{Operation Income} = N \times E \times P$$

where

- N = count of customers in market area(based on gravity model matrix)
- E = average consumption expense
- P = market penetration rate (0.2 0.4)

$$\text{Operation Expense} = A \times S$$

where

- A = rentable area (i.e. 0.8×building area)
- E = minimum sales income per square meter to pay off the building and operation fees within 40 years mortgage (assuming 10,000 RMB/m^2/year)

Step3: Test the accuracy using actual operating information from social media
This research created a metric to measure the operating performance using social media data. The operating metric equals the product of average customer consumption and number of comments of a single shopping center divided by the building area, which reflects the profitability per service unit.
I ranked the shopping centers by operating metric and subset X number of malls with smallest index labeled with high loss risk, while the rest of malls were labeled with low loss risk. By comparing the label with classification result from step 2, accuracy rate was output.

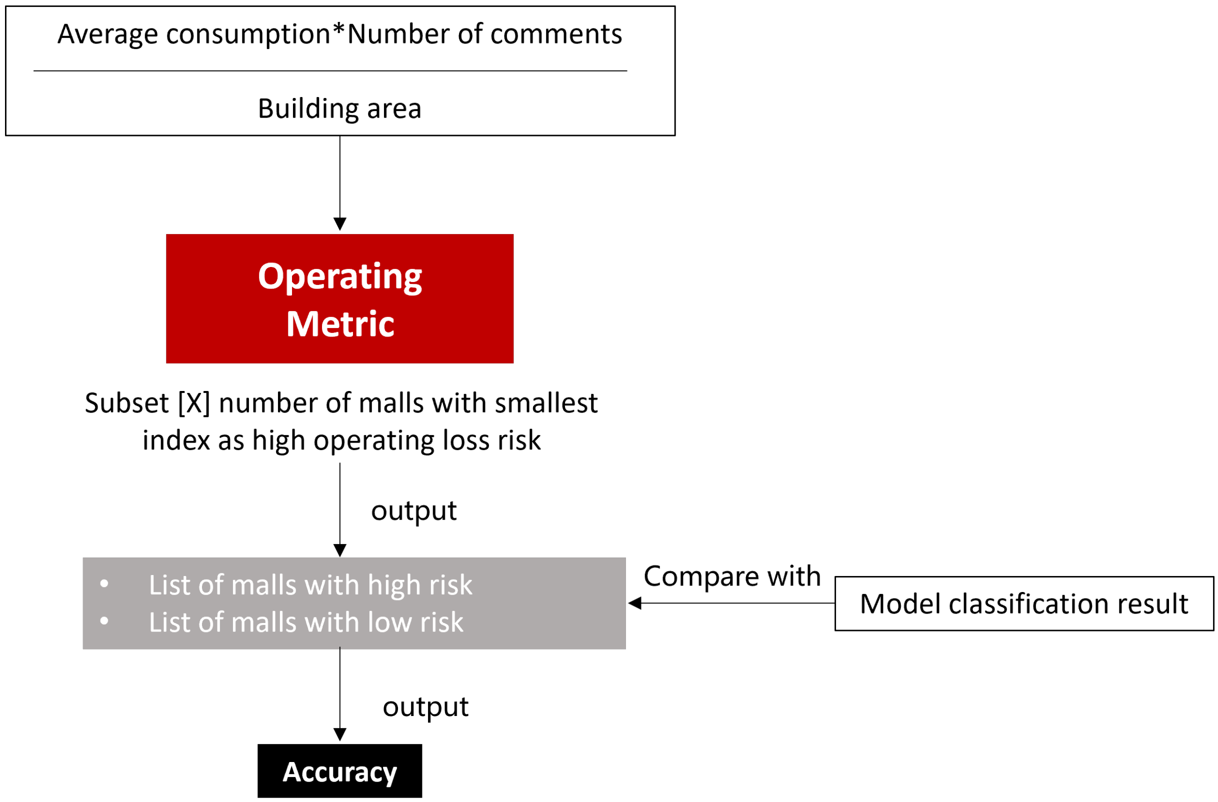

Figure 13: Pipline of Step 3

4.2 Analyzing mismatch of operation and location value

Step1: Quantifying location value using entropy weighted method
Amount of researches quantified the location value using urban and business data for the purpose of site selection (ELSamen and Hiyasat (2017); Roig-Tierno et al. (2013); Church (1999); Brown (1993)). Through reviewing the relevant papers and considering accessible data sets, I summarized four most widely considered perspectives, including transportation, amenity, demographic and competitive intensity, which contain 10 indicators in total. The detailed description of each indicator is explained in 2.

Categories	Factors	Description
Transportation	Subway	Distance to the nearest subway station
	Road density	Distance to 5 nearest crossroads
Amenity	Urban parks	Distance to the nearest parks
	Attractions	Distance to 3 nearest attractions
	University City	Distance to the nearest university city
Demographic	Population	Population density of neighborhood
	Consumption	Average annual consumption
Competition	Competitive intensity	Number of comparable shopping centers in 3km
	Competitiveness	Area of the shopping center divided by total area of the competitors within 3 kilometers

Table 2: Description of location value indicators

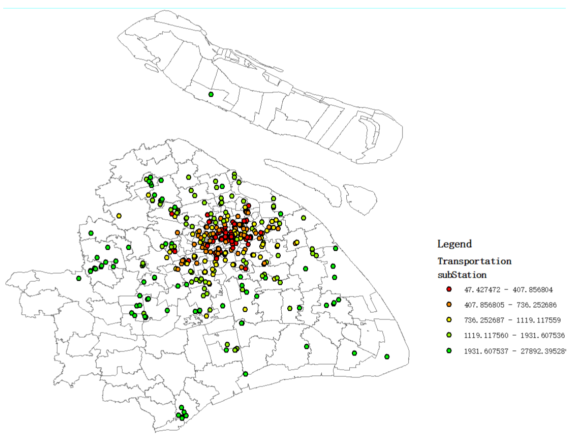

Figure 14: Distance to the nearest subway station

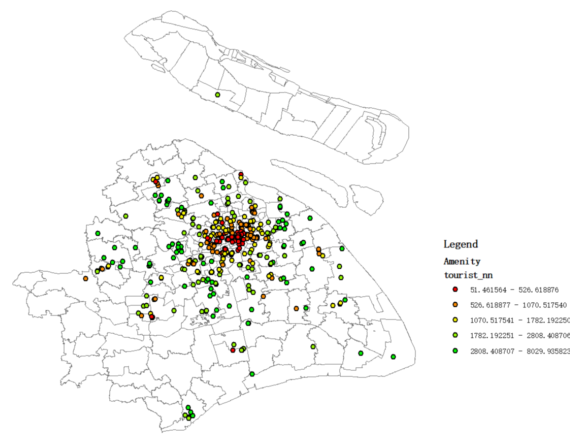

Figure 15: Distance to 3 nearest attractions

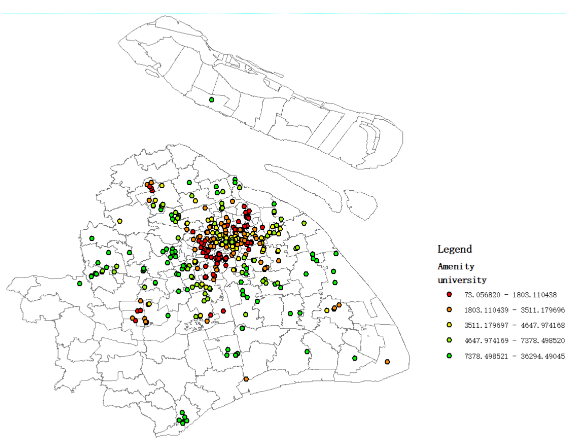

Figure 16: Distance the to nearest university city

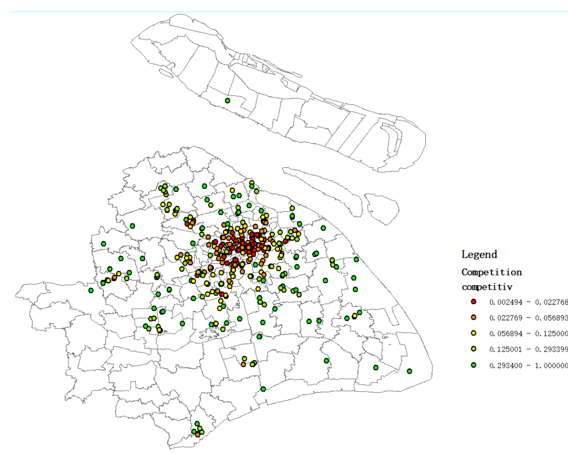

Figure 17: Competitiveness in 3km buffer area

Some insights can be summarized through visualizing the indicators.Generally speaking, shopping centers located in the city center have a greater location advantageespecially from the perspective of transportation. Seeing from 14, shopping centers in downtown are closer to subway station because of higher service coverage rate in this area. Meanwhile, suburban shopping malls also have location advantages in some way. For instance, shopping malls in Yangpu and Songjiang districts are closer to the university city 16. Malls located at urban periphery benefit from the spillover effects from the natural attractions 16. Moreover, suburban more are more competitive in the local neighborhood, since there are few competitors in the surrounding area 17.

Entropy weight method (EWM) was applied to weight these indicators. It is a commonly used weighting method that measures value dispersion in decision-making. Information is derived from the degree of dispersion. The range of entropy value is [0,1]. The larger the entropy value is, the higher weight should be given to the indicators. There are many researches using EWM to locate retail and facilities (Li and She (2010); Chen and Qu (2006); El-Araby, Sabry and El-Assal (2022)). To conduct EMW, the first step is to standardizing the data. In this research, I applied min-max scaling method to retain the variance.

$$P_{ij} = \frac{X_{ij} - \underset{i}{Min}(X_{ij})}{\underset{i}{Max}(X_{ij}) - \underset{i}{Min}(X_{ij})}$$

where

- X_{ij}=the value of the ith indicator in the jth sample.
- P_{ij}=the standardized value of the ith index in the jth sample.

For the next step, entropy value and weight of each indicator was calculated, Below is the equations and parameters of EWM referenced research of Zhu, Tian and Yan (2020):

$$E_i = -\frac{\sum_{j=1}^{n} P_{ij} \cdot \ln P_{ij}}{\ln n}$$

$$w_i = \frac{1 - E_i}{\sum_{i=1}^{m}(1 - E_i)}$$

where

- E_i=the entropy value of ith indicator.
- w_i=the weight ith indicator.
- m=number of indicators.
- n=the number of samples for the ith indicator.

Categories	Primary Weight	Factors	Entropy Weight
Transportation	0.3	Subway	0.22
		Road density	0.08
Amenity	0.2	Urban parks	0.09
		Attractions	0.06
		University City	0.05
Demographic	0.2	Population	0.18
		Consumption	0.02
Competition	0.3	Competitive intensity	0.13
		Competitiveness	0.17

Table 3: Entropy weight of location value factors

The results of entropy weight are shown in 3. The primary weight were controlled based on the Delphi method from relevant researches(ELSamen and Hiyasat (2017)). The secondary weight was calculated using EWM.
18 demonstrates the frequency of the calculated location value. As we can see, the plot is right skewed. Most of the shopping centers lie in the range from 0.125 to 0.2.

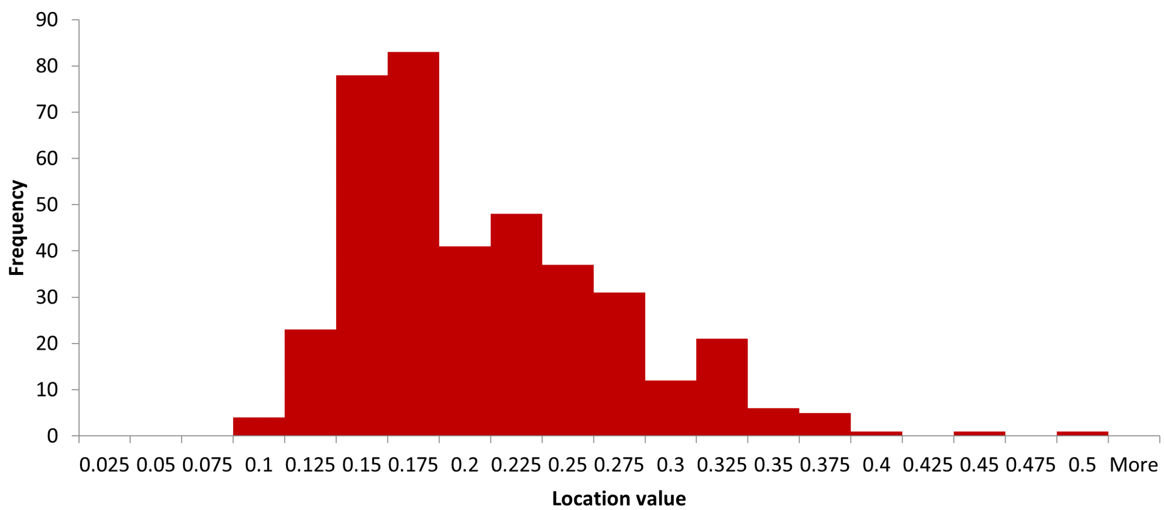

Figure 18: Frequency of location value

Step2: Building a regression model with operation and location value
For the next step, a regression model is built with operation and location value of each shopping center. The operation value referenced the operating metric created in the previous step. In the first model, all samples of shopping mall are included. As the 19 illustrates, the correlation between location and operation value is close to zero, which is counterintuitive. Tons of researches has proved the importance of location to the operation performance of

the retail.

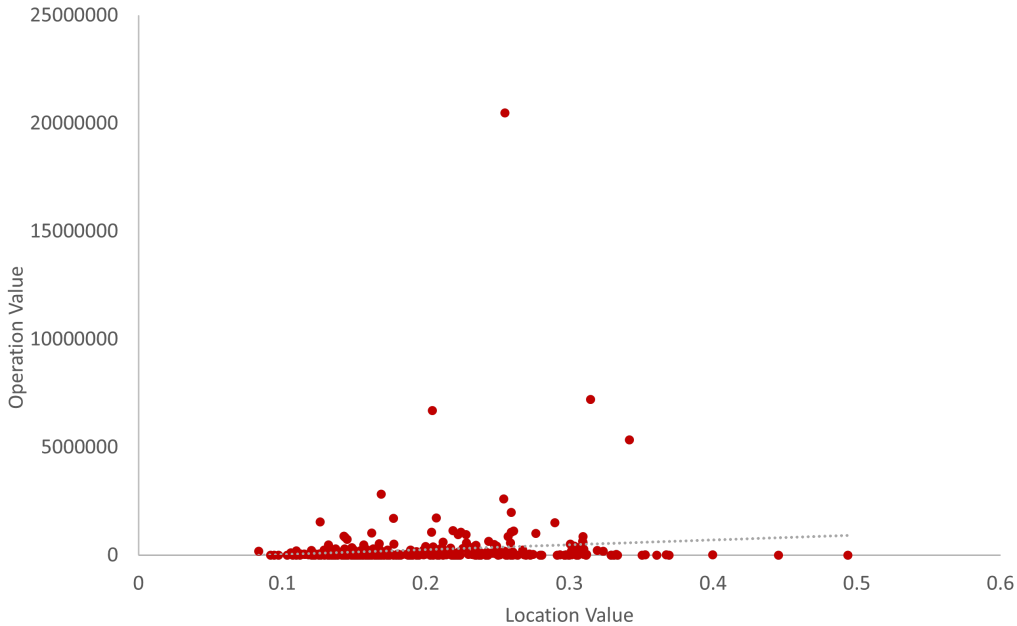

Figure 19: Operation value as a function of location value

Some data cleaning works were conducted following. Firstly, I cleaned the 3 luxury malls as outliers because their operation metric is so high. Then, I tried to split the data into 3 groups, low-end, mid-end and high-end malls, based on the average customer consumption 19. The threshold of classification is based on the distribution of data 9. A second trial is taken and 3 regression models were built separately. The result improved significantly through controlling the variable of average consumption of customers. Seeing from the series plots 20, for high-end malls, the operation value is highly correlated with location. This may because high-end malls are picky about their locations. Their target customers are from a large region, therefore the accessibility is an essential factor. As for the low-end malls, most of their target customers are from the local neighbourhood, so location is less important for them.

Class	Average Consumption(RMB)
High-end malls	$0 \leq x < 200$
Mid-end malls	$200 \leq x < 400$
Low-end malls	$x > 400$

Table 4: Classification of shopping malls

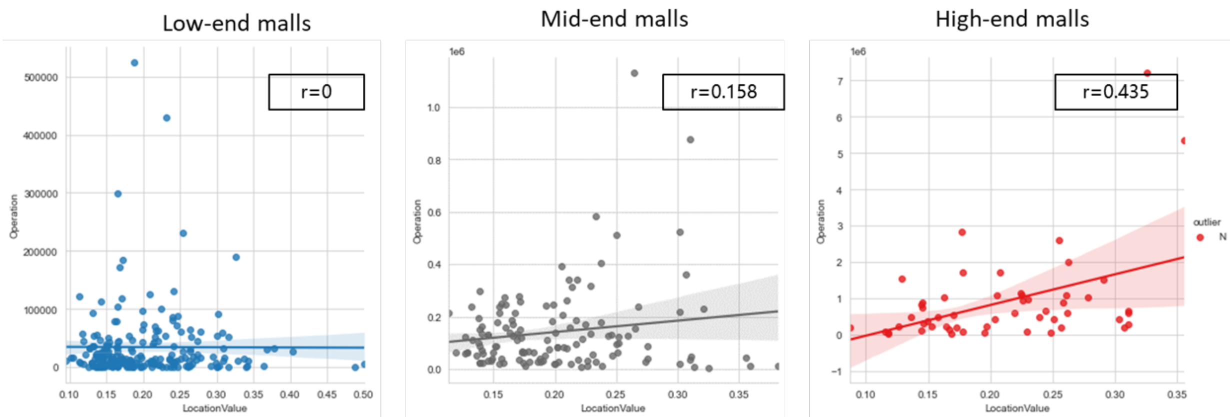

Figure 20: Frequency of location value

Step3: Detecting outliers under the regression line
In this research, outliers under the regression line are defined as shopping centers with redevelopment value. It means that the low operation value of these malls doesn't match the high location value comparing with other samples. Based on the statistical definition, if the residual is great than 2.5 times of the standard deviations from the mean, the shopping center is labeled as an outlier 21. There are 7 outliers detected in total. 4 of them are low-end malls and the remaining are mid-end malls 22.

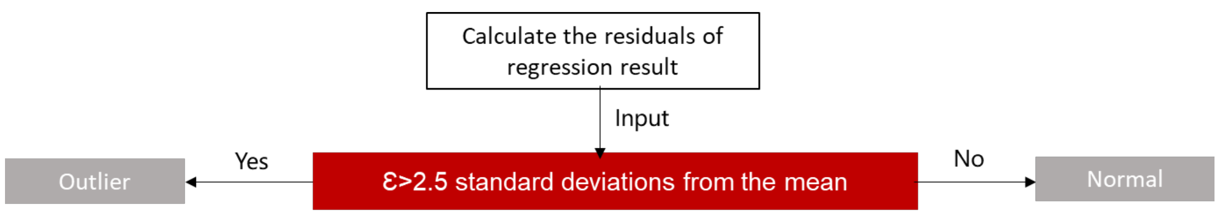

Figure 21: Pipline of Step 3

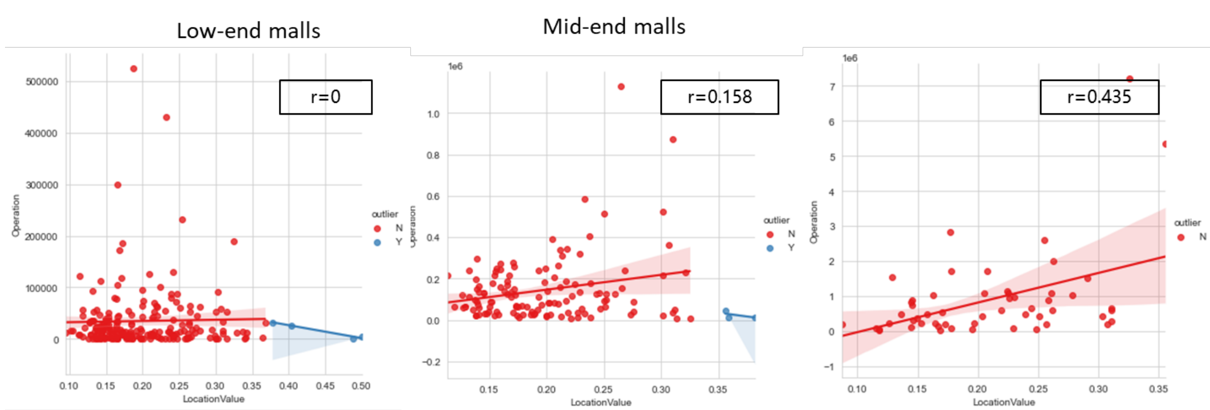

Figure 22: Frequency of location value

5 Results

5.1 Identified shopping centers with high operating loss risks

Two models were built to identify the operating loss risk. The difference of two models lie in the parameter of Huff model. In Model 1 (M1), D_{ij} is calculated based on the road network, while D_{ij} in Model 2 (M2) is calculated by straight-line distance. Though M1 reflects the real driving distance, M2 shows better performance in accuracy 22. This may because the low quality of road data. After checking the raw data, connectivity problems were detected at the junction of roads. Therefore, M2 was chosen as the final model.
The final model identified 57 shopping centers with high risk out of 392, which accounts for 15 percent. Seeing from the confusion matrix 23, the overall accuracy is 0.86. Since input data is before 2020 and accuracy test data is up to data. It seems that the model could predict loss risk before the construction of a new project. However, it has limited accuracy to identify shopping centers with high loss risk.

Labels	M1 Accuracy	M2 Accuracy
Overall	82.30%	86.22%
High operating loss risk	52.35%	50.87%
Low operating loss risk	90.05%	92.24%

Table 5: Accuracy of M1 and M2

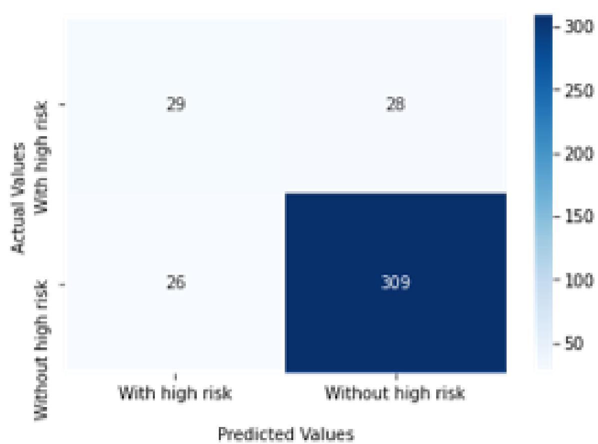

Figure 23: Confusion matrix of prediction results

Through visualizing spatial distribution of prediction results 24. Malls with high loss risk are mostly located in suburban areas where the aggregated consumption capacity is small. In these area, though there is less competition, the low population density and low-income groups may not offer the cost of operation.Some other identified malls are located in the

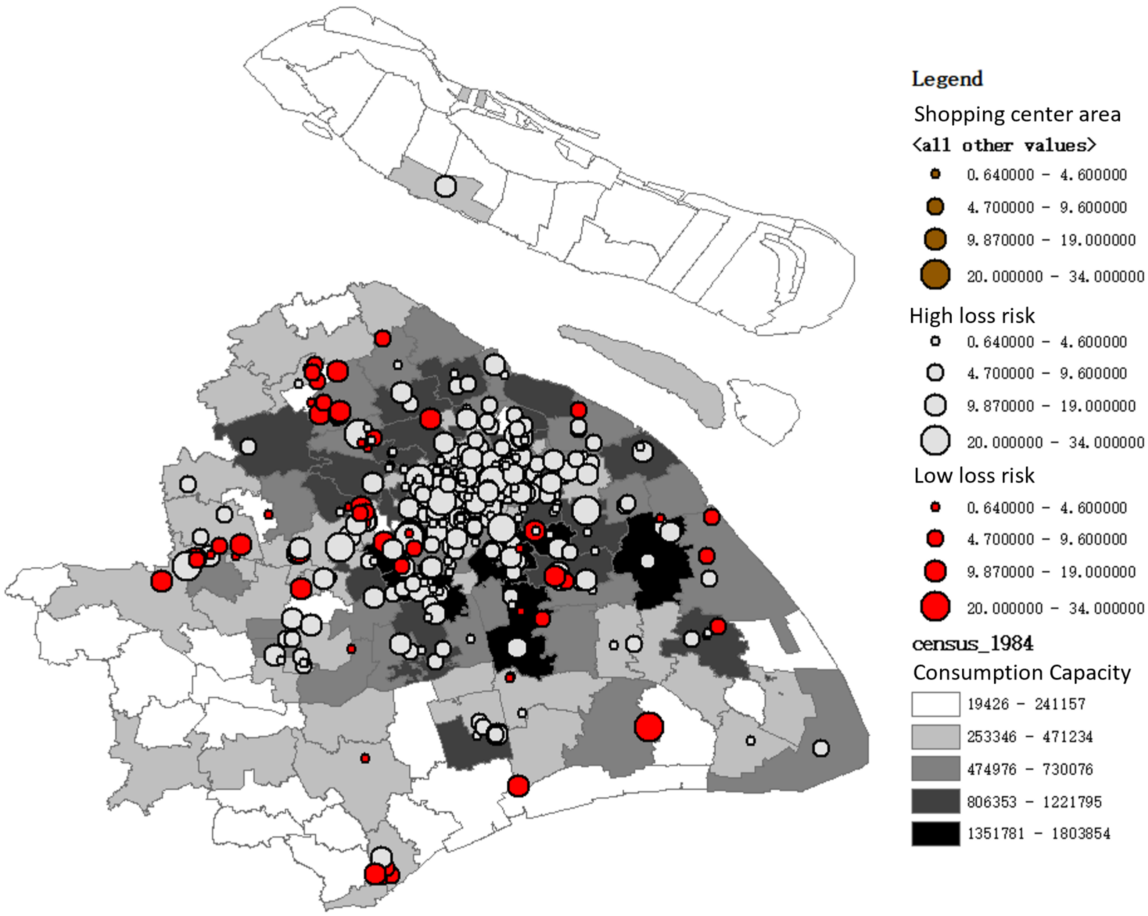

Figure 24: Spatial distribution of shopping malls with high loss risks

secondary center of the city, where the middle-class clustered in. The competition in these area is intensive and small scale malls are usually hard to survive.

Seeing from the spatial distribution of errors 25, there are some bias in current model. As we can see true-negative mistakes cluster in rich neighborhoods, while false-positive mistakes cluster in suburban communities where income is lower. This means that malls located in the high-income neighbourhoods are more likely to be labeled as low loss risk. On the contrary, shopping centers located in low-income area are more likely to be labeled as high loss risk. This is because the model considers spatial and social factors but ignores management influence. Some malls have a good location but still face the closing risk due to less competitive management capability.

5.2 Detected shopping centers with redevelopment potential

For the 7 detected malls with redevelopment potential. Redevelopment strategies are raised based on the mall type and competing environment. For the mid-end malls with surrounding

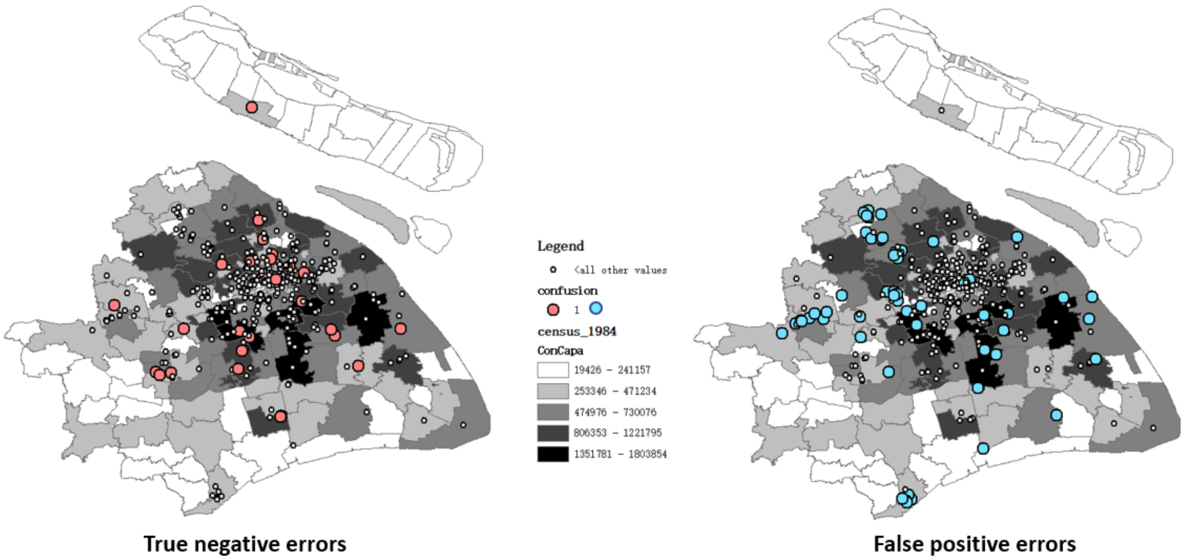

Figure 25: Spatial distribution of errors

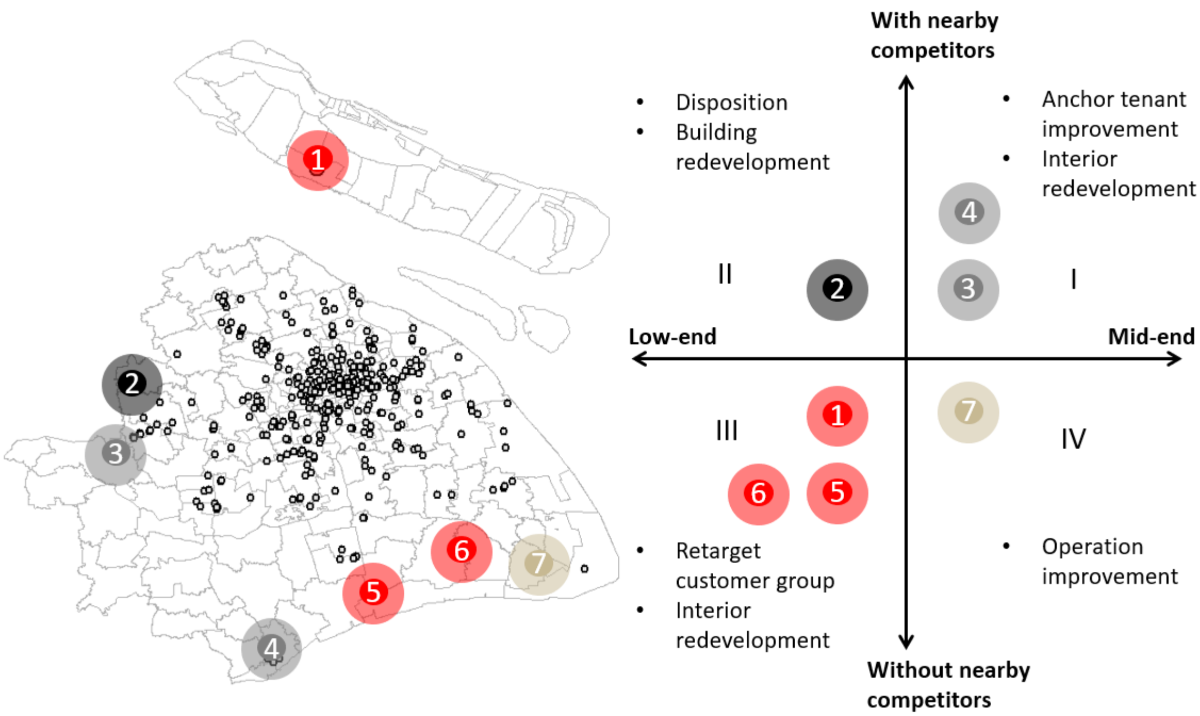

Figure 26: Strategies for the shopping centers with potential redevelopment opportunities

competitors (mall 3,4), to enhance their competitiveness they could find new anchor tenant and redevelop the interior. For the low-end malls with surrounding competitors (mall 2), since both of the building quality and location are not idea, they could consider disposition or change the building function. For the low-end malls without nearby competitors (mall 1, 5 , 6), since these malls have monopolized market in the local neighbourhoods, they could try to retarget customer groups and improve their attractiveness to the residents. As for the mid-end mall without nearby competitors, they could cooperate with experienced asset management companies to improve the operation income.

6 Discussion

From the results of data exploration, the spatial distribution of shopping is unevenly distributed. From the perspective of land use planning, commercial land should be planned based on the demand. However, the shopping malls in Shanghai are highly clustered in the downtown, which leads to unhealthy market environment. From a macro market perspective, the total building area of shopping centers in Shanghai is oversupplied based on the climbing vacancy rate. However, from a micro market perspective, residents have low accessibility to the shopping center in suburban area. This situation makes it rather important to identify the malls with high loss risks. In highly competitive areas, some malls could consider to redevelopment and change their building function to make profits. For the future projects, developers can reference this research to choose area where the operation loss risk is low. Therefore, this research helps to rebalance the market in the future.

The model identified 57 shopping malls with high loss risks, accounts for 0.15 of the total amount. However, the actual number could be even larger. The operation expense is estimate by the minimum sales income per square meter to pay off the building and operation fees within 40 years mortgage. In real world, the operation cost can be even higher, especially for the mid-end and high-end malls. The government should pay attention to this problem and make policy to encourage the redevelopment of malls with high loss risk.

There are some strengths in this study. Traditionally, operation risk is evaluated based on the historical cash flow of assets. However, cash flow numbers are usually not exposed to the public, which makes the competitors, researchers and government hard to learn the real market situation. This study create a brand new solution to estimate the operating loss risk using open data set with 0.86 accuracy. This framework is generalizable and can be applied to other cities. Besides, since the input data is historical data before 2020 and the test data is up to data. It proved the predictive capability of our model. Developers and investors could reference the result before acquire new project.

There are also some limitations. Firstly, the model considers spatial and social factors but ignores the influence of management. There is a bias toward the malls located in the rich and poor communities. Also, due to the low quality of road data, we failed to test if the model calculated by the network distance had better performance. Besides, impact of the pandemic is not considered in this model. In fact, there could be more than 57 shopping centers facing closing risk.

7 Conclusion

In an overbuilt market, shopping malls are facing higher loss risks. Focusing on the shopping malls in Shanghai, we built a model to identify the operating loss risk based on the Huff model and real estate financial formulas. The accuracy of final model is 0.86. To find out shopping center with redevelopment potential, this article analyzed the mismatch of the location value and operation value and detected 7 shopping centers. Our study create a new solution to estimate the operating loss risk using accessible public data. The framework is flexible and can be applied to any cities in the world. For the government, they could reference the results for commercial land planning and urban regeneration. For the investors, this model can be utilized for risk evaluation and help them seize the redevelopment opportunities. For the next steps, we plan to apply this model to other cities and test the generalizability of accuracy. Besides, we want make some extensions to the gravity model and find some powerful indicators to offset current bias issue.

Appendix

Supplementary data to this article can be found online at

https://github.com/CPLN-680-Spring-2022/Chi_Zhang_RetailwithLossRisk

References

Brown, Stephen. 1993. "Retail location theory: evolution and evaluation." *International Review of Retail, Distribution and Consumer Research*, 3(2): 185–229.

Chen, Yan, and Lili Qu. 2006. "Evaluating the selection of logistics centre location using fuzzy MCDM model based on entropy weight." Vol. 2, 7128–7132, IEEE.

Church, Richard L. 1999. "Location modelling and GIS." *Geographical information systems*, 1: 293–303.

Dong, Wan. n.d.. "Behavior of Local Government and Real Estate Development——An empirical study of Shanghai."

El-Araby, Ahmed, Ibrahim Sabry, and Ahmed El-Assal. 2022. "A Comparative Study of Using MCDM Methods Integrated with Entropy Weight Method for Evaluating Facility Location Problem." *Operational Research in Engineering Sciences: Theory and Applications*, 5(1): 121–138.

ELSamen, Amjad Ahmad Abu, and Rund Ibrahim Hiyasat. 2017. "Beyond the random location of shopping malls: A GIS perspective in Amman, Jordan." *Journal of Retailing and Consumer Services*, 34: 30–37.

Jian Sheng, Li. 2020. "In the stock era, the winning way of commercial real estate." *https://www.oliverwyman.cn/our-expertise/insights/2020/nov/the-way-to-success-in-commercial-real-estate.html*, Accessed: 2022-04-27.

Kim, Pan-Jin, Wanki Kim, Won-Ki Chung, and Myoung-Kil Youn. 2011. "Using new Huff model for predicting potential retail market in South Korea." *African Journal of Business Management*, 5(5): 1543–1550.

Kohonen, Aleksi, et al. 2015. "Management of unsystematic risks in commercial real estate asset management." Master's diss.

Li, Jiangtao, Jianyue Ji, Huiwen Guo, and Lei Chen. 2018. "Research on the influence of real estate development on private investment: a case study of China." *Sustainability*, 10(8): 2659.

Li, Tao, and Lian She. 2010. "Retail location decision-making based on the combination of AHP and Entropy Weight." Vol. 1, 136–139, IEEE.

Roig-Tierno, Norat, Amparo Baviera-Puig, Juan Buitrago-Vera, and Francisco Mas-Verdu. 2013. "The retail site location decision process using GIS and the analytical hierarchy process." *Applied Geography*, 40: 191–198.

Suárez-Vega, Rafael, José Luis Gutiérrez-Acuna, and Manuel Rodríguez-Díaz. 2015. "Locating a supermarket using a locally calibrated Huff model." *International Journal of Geographical Information Science*, 29(2): 217–233.

Su, Shuai, and Myoung-Kil Youn. 2011. “Using Huff Model for Predicting the Potential Chiness Retail Market.” *Asian Journal of Business Environment*, 1(1): 9–12.

Wei, Wang. 2021. “0.3m^2 per capita shopping center area: the current cordon of domestic cities.” *http://www.linkshop.com/news/2021462844.shtml*, Accessed: 2022-04-27.

Yingshang.com. 2020. “More than 200 shopping centers closed in China.” *https://new.qq.com/omn/20191122/20191122A0QTLR00.html*, Accessed: 2022-04-27.

Yun, Cai. 2021. “Oversupplied Shopping Centers in China.” *http://www.chinashangcan.com/newsshow.asp?id=1141&big=1*, Accessed: 2022-04-27.

Zhang, L. 2013. “The Development Upsurge in Foushan.” *Real Estate Guide*, 4.

Zhu, Yuxin, Dazuo Tian, and Feng Yan. 2020. “Effectiveness of entropy weight method in decision-making.” *Mathematical Problems in Engineering*, 2020.