PORTRAYING FOOTWEAR CUSTOMER ENTER -STORE BEHAVIOR IN CHINA: BASED ON COMPUTER VISION TECHNOLOGY

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ABSTRACT. Existing studies on customer behavior lack quantitative and high efficiency study, their technologies rely heavily on hardware. Therefore, the information of consumers in offline stores was insufficient, which made enterprises unable to accurately track consumers. However, computer vision (CV) is an expert in identifying and tracking people's behavior, and its function is suitable for investigating enter-store customer behavior. Therefore, the aim of our study was to develop an offline consumer behavior portraying system based on CV. Then we used this system to investigate enter-store consumption behavior. We selected 71 shoe stores in China, then installed the system in store for a three-month data collection, and evaluated the impact of customer's age, gender, enter time, and region factors on enter-store behavior in China. Through our system, we successfully study ways to improve the purchase conversion rate of enter-store consumers, which could guide enterprises to adjust better marketing and operation strategies.
KEY WORDS: customer behavior, computer vision, off-line retailing, enter-store data collection

CARACTERIZAREA COMPORTAMENTULUI CLIENTULUI LA INTRAREA ÎN MAGAZINELE DE ÎNCĂLȚĂMINTE DIN CHINA: PE BAZA TEHNOLOGIEI VIZIUNII COMPUTERIZATE

REZUMAT. Cercetările existente privind comportamentul clienților nu prezintă un studiu cantitativ și de înaltă eficiență, tehnologiile utilizate se bazează foarte mult pe hardware. Prin urmare, informațiile privind consumatorii care achiziționează din magazinele fizice sunt insuficiente, ceea ce face ca întreprinderile să nu poată urmări cu precizie consumatorii. Cu toate acestea, viziunea computerizată (CV) este o tehnologie expertă în identificarea și urmărirea comportamentului oamenilor, iar funcția sa este adecvată pentru investigarea comportamentului clienților din magazin. Prin urmare, scopul studiului nostru a fost dezvoltarea unui sistem offline de caracterizare a comportamentului consumatorului pe baza CV. Apoi am folosit acest sistem pentru a investiga comportamentul consumatorului în magazin. Am selectat 71 de magazine de încălțăminte în China, apoi am instalat sistemul în magazin pentru o colectare de date de trei luni și am evaluat impactul factorilor precum vârsta, sexul, timpul de intrare și regiunea asupra comportamentului clienților la intrarea în magazinele din China. Cu ajutorul sistemului nostru, am studiat cu succes modalitățile de îmbunătățire a ratei de conversie în cazul consumatorilor din magazin, care ar putea servi ca ghid pentru întreprinderile care vor să-și îmbunătățească strategiile de marketing și de operare.
CUVINTE CHEIE: comportamentul clientului, viziune computerizată, comerț cu amănuntul offline, colectarea datelor la intrarea în magazin

LA CARACTÉRISATION DU COMPORTEMENT DU CLIENT LORS DE L'ENTRÉE DES MAGASINS DE CHAUSSURES EN CHINE : BASÉ SUR LA TECHNOLOGIE DE VISION PAR ORDINATEUR

RÉSUMÉ. Les recherches existantes sur le comportement des clients ne présentent pas d'étude quantitative et très efficace, les technologies utilisées sont largement basées sur le matériel informatique. Par conséquent, les informations sur les consommateurs qui achètent dans des magasins physiques sont insuffisantes, ce qui empêche les entreprises de suivre avec précision les consommateurs. Cependant, la vision par ordinateur (CV) est une technologie experte dans l'identification et le suivi du comportement des personnes, et sa fonction est adaptée pour enquêter sur le comportement des clients dans le magasin. Par conséquent, le but de notre étude était de développer un système hors ligne pour représenter le comportement des consommateurs basé sur le CV. Ensuite, on a utilisé ce système pour enquêter sur le comportement des consommateurs dans le magasin. On a sélectionné 71 magasins de chaussures en Chine, puis on a installé le système dans le magasin pour une collecte de données de trois mois et on a évalué l'impact de facteurs tels que l'âge, le sexe, l'heure d'entrée et la région sur le comportement des clients lors de l'entrée dans les magasins en Chine. Avec l'aide de notre système, nous avons étudié avec succès des moyens d'améliorer le taux de conversion des consommateurs en magasin, ce qui pourrait servir de guide aux entreprises qui souhaitent améliorer leurs stratégies de marketing et d'exploitation.
MOTS CLÉS : comportement du client, vision par ordinateur, vente hors ligne, collecte de données à l'entrée du magasin

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INTRODUCTION

Enter-store consumers' consuming behaviors referred to a series of complex psychological characteristics and behavior rules generated by the enter-store customers [1]. The diverse consumer psychology of customers would affect their consumption decision. Jackson *et al*. [2] proposed that the psychology of consumers of different genders and age groups led to certain differences in their attitudes towards shopping. Kahler *et al*. [3] reported that the values and other psychological variables of people in different regions would lead to regional psychological and behavioral differences in customer behaviors. Then, consumers' in-store activities would also affect consumption decisions. If consumers were actively processing information to trigger new demands, so many unplanned purchase decisions would be occurred in the store [4]. Pantanoa *et al*. [5] also noted that after increasing product contact, leisurely consumers would browse a wide range of the store, which led to more purchase. Moreover, understanding offline customer's behavior is important to retailing store which provided services to enter-store people [6]. Therefore, enter-store customer behavior studies is becoming critical.

Commonly, most consumer studies were taken by questionnaire surveys, which were not objective and the sample size was limited. Thang *et al*. [7] carried out a study on the influence of in-store factors on consumer behaviors and distributed 370 questionnaires with the invalid rate of 21.6 percent. Besides, Bucko *et al*. [8] used number 1-5 to describe the consumers' willingness to purchase product from the online store to obtain the factors of affecting consumer behavior, only 232 people collected. What is more, there were series of other tracking consumers methods such as infrared, RFID, and video technology [9–11], but these methods highly depended on high cost hardware.

At present, the commercial technology used to study customer behavior in offline stores is mainly focused on the people counting. There are two main techniques for people counting: infrared technology and video flow counting. Infrared technology has high dependence on equipment. Jie *et al*. [9] invented an infrared photoelectric counting device with a high cost and low software resolution. Yang *et al*. [12] designed a better accuracy infrared counting device, but the installation process of the equipment was cumbersome. Meanwhile, the video flow technology also can count the number of people. Haritaoglu *et al*. [13] proposed a real-time camera recognition system to capture, track, and identify people walking. Masoud *et al*. [14] studied a fixed single-camera to identify pedestrians and achieved reliable counting by suspending it from the ceiling, which was based on a rectangular model of human motion analysis. However, most surveillance devices in life were only used for security [15].

Thereby, the infrared technology highly dependents on hardware and costs, while the video technology has a low application potential in the retail industry. In the previous study, the factors that affect enter-store consumer's behavior were lack of quantitative research and the results were also subjective and vogue, which also leads to customer's purchase conversions remains a great challenge [16, 17].

To further effective study offline customer behavior, we found that the computer vision (CV) was suitable to identify and track people in the store [18, 19]. However, the application of CV on the retailing stores was rarely reported. Due to lots of large shopping malls and brands were eager to adopt a technical solution to detect these three aspects automatically: customer counting, customer's attribute recognition, behavior understanding [5, 10]. We briefly introduced the realization methods of the three functions of CV.

1. Customers counting. The video stream counting was by tracking the images of the moving human body in the video sequence [13], which was one of the applications of computer vision. The counting steps of the video stream [20] were video capturing, video editing, mobile personnel monitoring, mobile personnel tracking, and people number calculation [21]. At the same time, this function has been widely used in daily life, such as real-time passenger flow calculation [22] of subway, bus and so on.

2. Identify people's attributes. As one of the typical applications of computer vision, facial recognition technology can not only count people but also recognize their attributes. The main process of it [23] were facial detection (feature point location), facial tracking, facial recognition

(gender and age recognition), Besides, Generosis *et al*. [16]proposed an emotion tracking system combined with facial recognition to detect customers' gender, age, and other information. The identified information belonged to the attribute information of consumers, which can help the store to know more accurately about their own consumers.

3. Description of human characteristics. The analysis, understanding, and description of customer behavior in changing environment were popular in the field of CV study. For example, Mckenna *et al*. [24] investigated a CV system that could track multiple people in a relatively unrestricted environment. Li Liyuan *et al*. [25] proposed a CV system successfully tracked about 90% of objects in a multi-person environment in a specific area. Besides, a real-time visual monitoring system invented by Haritaoglu *et al*. [13] could interpret the events between people and objects, by storing, exchanging or removing the objects.

In the complex and ever-changing offline buying environment, these three functions of CV technology were significantly suitable for offline research on consumer behavior.

Therefore, the aim of this study was to establish a consumer behavior portraying system based on CV. Then this system was used to conduct the enter-store customer behavior investigation. If we understand the preferences and rules of offline customers, companies can segment customers more accurately and update their marketing strategy timely in China.

METHODS

In this study, we cooperated with Red Dragonfly, a well-known footwear brand in China. We selected 71 from their 4,000 offline stores and proceeded to install our CV system, where eight in Central China, six in East China, forty-one in West China; and sixteen in South China. We also classified the data according to these four regions. The data collection period was from April 2017 to July 2017.

The structure of this system was shown in Figure 1. When customers entered the store, the video flow captured by cameras, was transited to the cloud server in real-time through the wired connection of the router. Then the cloud server processed the video data and stored the results in the cloud database so that we could use the algorithm integrated into cloud computing to analyze the data.

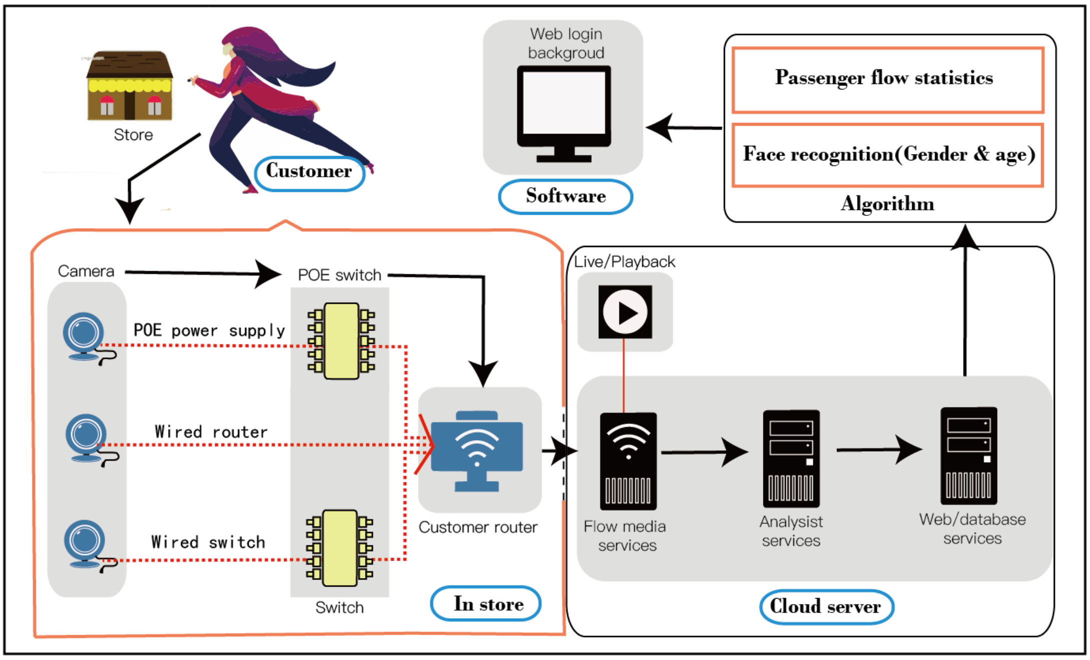

Figure 1. The detailed system operation diagram

Algorithms

The algorithms used in the data recording system in this study were provided by the Extreme Vision company, which is a professional computing vision supplier in China. The algorithm was divided into two parts: people counting; and identifying the gender and age.

Data Collection of Passenger Flow

The whole process of algorithms counting customer number was:

(1) Recognizing the moving subjects using foreground detection

The complex background is subtracted by foreground detection to simplify the image. The mixed Gaussian model in the background modeling method could smoothly simulate the probability distribution of any shape and handle the extraction of foreground under complex background;

(2) Detecting the head of the customers enter-store in the video.

A rectangle with green lines was used to identify their head, and then established a recognition frame on their head, and marked with a green line. Then the area of the entrance in-store was marked with a rectangle with blue lines, the yellow line as an analysis basic-line;

(3) Counting the valid number.

Figure 2-b shows that once the customers pass by the analysis base-line, a new valid number was recorded. Instead, Figure 2-c represents the invalid case.

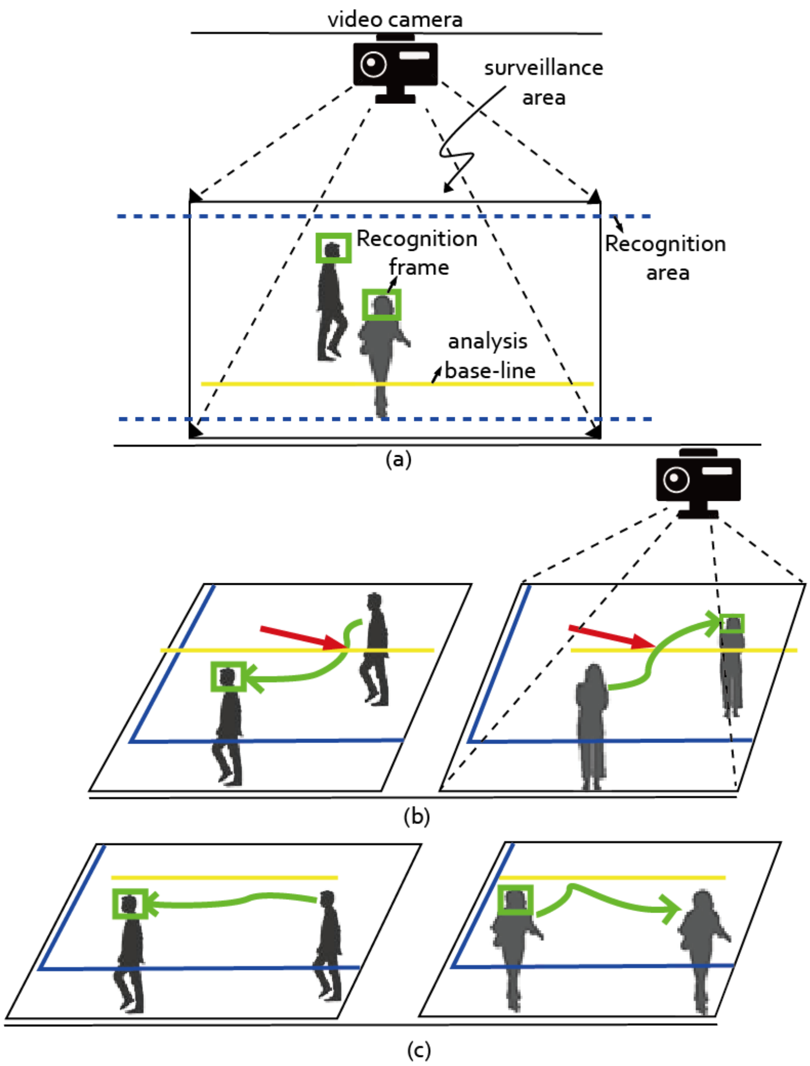

Figure 2. a) Introduction of the camera recognition; b) The entrance and exit were valid number statistics; c) Pass by and hover were not counted

Data Collection of Facial Identification

We used the face recognition algorithm to recognize the customers' gender and age. There were three steps to the face recognition process: 1. Detecting and tracking the face in each frame of video; 2. Obtaining the face movement in each frame of video, extracted the face feature points; 3. Analyzing the face feature using the face database to get the result.

(1) Gender identification

Compared to recognition based on the single gray channel information, the increased color features of the gender recognition technology used in this study improved the accuracy of gender recognition. The detailed gender determination process was:

a) Based on the multi-channel convolutional neural network technology, we obtained the RGB image of the face from the video and processed it to obtain multiple color channel information;

b) Input multiple color channel information into the convolutional neural network obtained in advance for calculation, and obtained an output result representing gender;

c) When the output result indicating gender was within the first preset range, the face gender was identified as male; when the output result indicating gender was within the second preset range, the face gender was identified as female.

(2) Age estimation

We built a face age estimation model based on multi-output convolutional neural networks to estimate customers' age. It combined ordered regression and deep learning methods to significantly improved the accuracy of age prediction performance. The specific implementation steps were:

a) Established an Asian face data set, each face image contained a real age label;

b) Established training data for binary classification, input face image sets with age tags in the Asian face data set, and generated a series of binary classification labels based on the age tags of the face images, for training data for class labels and weights;

c) Trained the deep convolutional neural network, and trained the multi-output deep convolutional neural network according to the training data, so that each output was a binary classification target of the binary classifier;

d) Input the test sample into the trained convolutional neural network, used a face image without age label in the Asian face dataset as the test sample, and input the test sample into the trained multi-output deep convolution Neural network for multi-layer convolution and pooling operations;

e) Got the age estimate of the test sample and the age of the test sample estimate. The overall steps were shown in Figure 3.

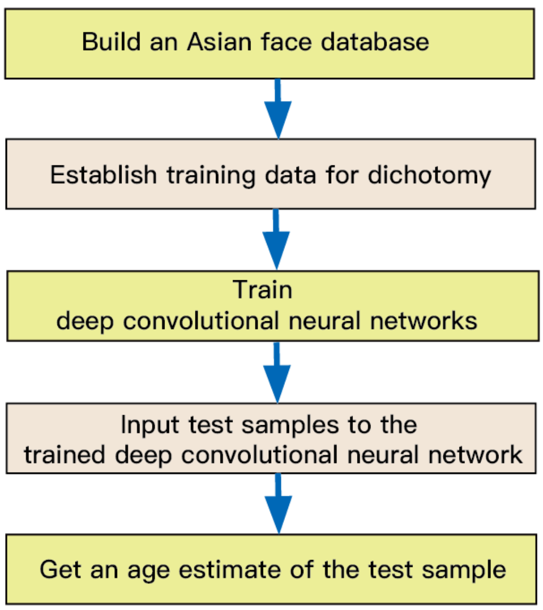

Figure 3. Flow chart of age estimation for multi-channel convolutional neural network

Data Processing and Statistical Analysis

All data normally distributed. The data collected were three types: the number of customers at different periods, the gender and age information of the consumers enter-store. The data was collected between 8:00 and 21:00 each day; the age was divided into the following five groups: under 20, 21-30, 31-40, 41-50, and over 51 years old. The descriptive analysis and One-Way ANOVA were used in this study. Since the consumer's enter-store behaviors were influenced by variables of customers' attributes, the independent variable was the number of customers, and the dependent variables were the time, age, gender, and regions. Further, this model was operated using SPSS (V24.0, IBM, USA) with a significant level of α=0.05 and a confident interval of 95%.

RESULTS

Table 1: Table of store entry in four regions

Aera		All	Central	East	South	West
Average daily number of customers of a single store		\	140	324	154	118
Sex ratio (women:men)		42:58	68:32	60:40	67:33	51:49
Age structure	Under 20	13.70%	10%	15%	12%	15%
	21-30	38.40%	36%	31%	50%	37%
	31-40	29.60%	35%	34%	24%	29%
	41-50	12.10%	14%	11%	10%	13%
	Over 51	6.20%	5%	9%	4%	6%

The cumulative monthly customer' number of all stores in this study was 321390. All subsequent results were monthly averaged for further analysis (Table 1). We conclude that the main customers of Red Dragonfly were aged 21-40. And customers in East China were the most active among the four regions.

Figure 4. Comparison of the time variation of customers' entering stores in four regions

From Figure 4, there were three peaks in the shopping time trend of all consumers, 10:00, 15:00, and 20:00. The customers aged 21-30 years old entered the store at 19:00 in East China, at 20:00 in South China, at 17:00-19:00 in Central China, at 10:00 and 15:00-16:00 in Western China. Then followed by customers ages 31-40. They preferred to visit during 17: 00-19: 00 in East and West China, while that was concentrated during 14:00-16:00 in South and West China.

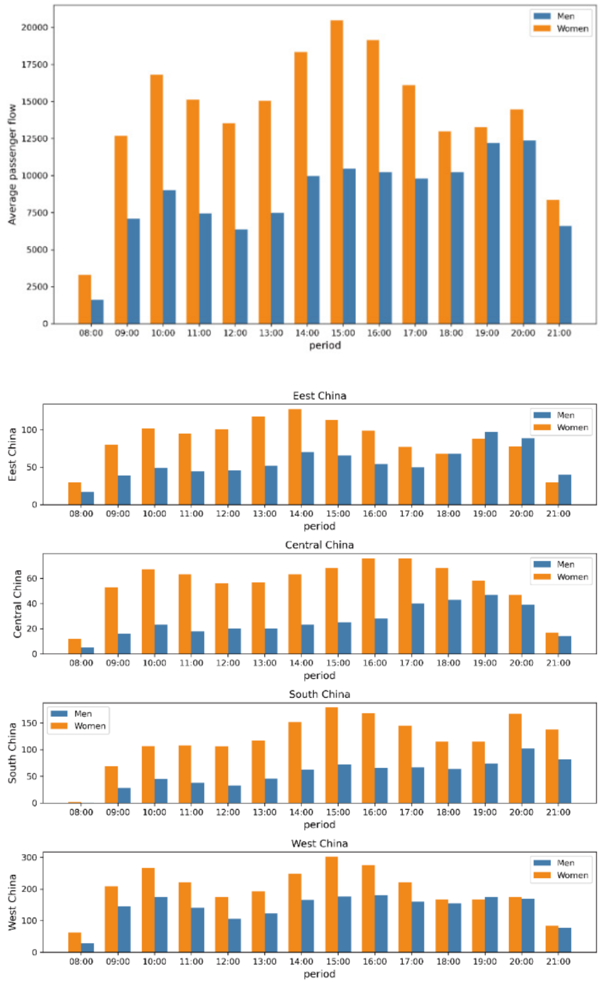

Figure 5. Results of different genders entered store at different times

From Figure 5, women except in central China more willing to shop at 16:00-17:00, they preferred shopping at 14:00-16:00 in other regions. Additionally, the number of women would increase significantly at 20:00 in South China. However, in Central China and Western China, their number would decrease from 18:00. Meanwhile, largest male customer flows were mainly concentrated in 19:00-20:00. Moreover, they were concentrated visiting at 19:00-20:00 in East and Central China, especially in East China. In general, the proportion of men and women should be more balanced.

One-way ANOVA Results

When considering the differences of time, age, gender, regional and the number of customers separately, the time (P = 0.01 <0.05) and age (P = 0.00 <0.05) have significant influence. Further, when we considered the combination of time, age, gender, and region in pairs, there were five combinations: time and gender (P = 0.00 <0.05), time and region (P = 0.00 <0.05), time and age (P = 0.00 <0.05), gender and region (P = 0.00 <0.05), age and region (P = 0.00 <0.05). Significant impacts were found in all the five groups above. In general, under the same time and region conditions, genders (P = 0.02 <0.05) had a significant effect on number of enter-store customers, but ages (P = 3.45> 0.05) had no significant difference in enter-store behavior.

DISCUSSION

In this study, our experience proved that CV technology was reliable, which was also confirmed by other research. Firstly, compared with other tracking technologies, the CV technology could realize real-time and efficient data collection [26]. Secondly, compared with the traditional survey, we had a larger sample base contained more than 300000 people. These cases prove that our CV technology, enriches the research methods of offline customer behavior as a technical supplement, and then it can help enterprises quickly realize the digital transformation [27].

In addition, the data results could give us a deeper understanding of regional differences in consumer behavior and heterogeneity. We were not surprised that most of the customers entering the store were female [28]. The reason for this phenomenon was related to the product and brand. Grohmann [1] proposed that the brand spokesperson had created a brand's personality, which was related to the consumer's gender role identity and emotion. Red Dragonfly's brand ambassadors have always been women, so this would lead a positive impact on women's responses. Meanwhile, the sexes had different consumption psychology and led to different products shopping attitudes [29]. Women would pay more attention to emotional and appearance needs. As well the shoes in Red Dragonfly have stronger appearance attributes and lower functionality. Fugate *et al*. [30] also proposed that women were willing to buy accessories, such as shoes, while men were preferred to buy products that match their gender, such as electronic products, etc.

Furthermore, there were obvious differences in the characteristics of consumers in each region. It indicated that the differences in living habits and regions would affect the basic consumer behavior of consumers. It also helped to verify Liu *et al*.'s view that China's consumer market was a segmented market with huge territorial and regional differences. Then among the average daily customer flow of separate stores in the four regions, East China was the most active. This may be due to the fact that Southeast China was considered to be a trend leader, an opinion leader, and a consumer pioneer in other parts of China. In contrast, consumers in central and southwestern China have lower incomes than in southeast coastal areas whose were generally satisfied with their lives and relatively conservative, not so willing to try fresh products [31]. Therefore, when new products were launched in chain retail stores, products should priority be placed in East China and South China. This could drive consumption benefits in Central China and West China.

In summary, our findings would assist the company flexibly arrange personnel for a specific period. Company should pay more attention to promoting the transaction conversion rate of the female, by increasing lively activities to attract young people enter in the evening. Our study also had shortcomings. On the one hand, the accuracy and convenience of video recognition should be improved. On the other hand, more factors affecting consumer behavior should be considered. Therefore, with the support of CV technology, the next steps are to study in-depth the detailed customers' trajectories or actions and complement the research on consumer decision-making mechanisms.

CONCLUSION

Our study aimed to develop a CV system to count and portray enter-store consumer attributes, then use this system to investigate offline customer behavior in Chinese different region. We selected 71 stores of Red Dragonfly and installed the system in them for a three-month data collection. And based on the geographical location of these stores in China, we divided them into four regions for later data analysis. Further, we evaluated the impact of customer gender, age, and time in regional stores on the number of customers. Finally, by our CV system, we found that the characteristic behaviors and influencing factors of consumer groups within four regions were indeed different.

Therefore, according to the findings of detailed customer behavior differences, enterprises can make accurate operational decisions to increase the chance of consumers' purchasing. Meanwhile, this method can also be used as a scientific and effective standard to explore ways to improve the purchasing probability of enter-store consumers, and then it can be widely used in the offline retail industry.

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