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Research Article

The Impact of E-Commerce and Ride Hailing on Emissions from Shopping-Related Transport: A Case Study of the Shopping Habits of University Students from Ningbo University

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To clarify the impact of new transport services on consumers' shopping behaviors and shopping-related transport emissions, a back-propagation neural network shopping channel choice model is established to estimate the number of times that consumers engage in online and offline shopping. A brick-and-mortar store choice model and travel mode choice model are developed, and a method to measure the quality of life of consumers is established to evaluate the impact of new transport services on shopping behaviors and the corresponding shopping transport emissions. The findings reveal that a new passenger transport service increases the number of times that consumers shop in brick-and-mortar stores and correspondingly shopping transport emissions; a new commodity transport service reduces the number of times that consumers shop in brick-and-mortar stores and in turn shopping transport emissions. In a scenario with both new commodity services and new passenger transport services, although online shopping is convenient, consumers are still willing to pay travel expenses for offline shopping; in a scenario with the new commodity transport service but without the new passenger transport service, the emissions from shopping-related transport are the lowest.

1. Introduction

Due to rapid urbanization and motorization, transport demand and the corresponding CO_2 emissions have increased considerably. Transport-related emissions have become a primary source of pollution, and energy savings and emission-reduction issues have been observed in the transport sector [1–4]. Moreover, with the development of Internet technology, "Internet +," a new economic form that integrates Internet technology and traditional industries, has penetrated transport services and retail businesses to generate new transport services, such as online car hailing, bicycle sharing, and car sharing. Theoretically, the combination of e-commerce and the related logistical services can also be regarded as a new commodity transport service because e-commerce offers channels for transactions among consumers, retailers, and producers, and e-commerce logistics are used to transport and deliver commodities.

New passenger services from transport network companies (TNCs), such as Didi Travel (which is the largest Internet TNC in China providing online car-hailing services) or Uber, match demand and supply between passengers and drivers based on real-time information, thereby reducing the empty trips of service vehicles and shortening passenger waiting times. Compared with traditional taxis, TNC services can save energy and reduce emissions [5, 6], while they also have induced new travel demands and thus increased carbon emissions. E-commerce and the corresponding logistical services enable consumers to purchase commodities and obtain delivery services at any time. Due to e-commerce, some discrete personal shopping trips have been replaced by centralized delivery traffic, thus reducing shopping travel demand and emissions. TNCs have changed consumers' shopping trips, and e-commerce has induced changes in their shopping channels. As a result, new transport services, such as TNCs and e-commerce with delivery, have changed shopping-related transport demand and carbon emissions. However, these changes have also shifted consumers' tendencies with respect to the utilitarian value and hedonic value because, due to the experience economy and service economy, consumers no longer simply pursue the utilitarian value embodied in the commodity itself but pursue the hedonic value embodied in the shopping process. When consumers experience a poor shopping atmosphere, they will have a sense of loss due to the unfavorable shopping experience and in turn reduced the shopping value, which may become a psychological obstacle and affect their shopping behavior. Therefore, it is of theoretical and practical value to study the impacts of new transport services on consumer shopping behaviors, shopping trips, and shopping-related carbon emissions.

To analyze the impact of new transport services on emissions from shopping-related transport, this study sets four shopping scenarios for consumers: (1)with new commodity transport services but without new passenger transport services, (2) with both new commodity transport and passenger transport services, (3) without new commodity transport services but with new passenger transport services, and (4) without new commodity transport or passenger transport services. Then, considering as target consumers the university students who had first lived on the main campus for two years were then relocated to a remote new campus for another two years, and a method is developed to quantitatively analyze the relationships between consumers' total shopping expenditures (cost of purchasing commodities and shopping transport services) and their quality of life (QOL).

In China, university students study and live on campus with financial support from their parents, and they rarely leave campus except to shop. Students' QOL is primarily determined by campus living conditions and their shopping satisfaction [7]. Since the living conditions at the new campus are as good as those at the main campus, the QOL of students who are relocated to the new campus is primarily determined by shopping satisfaction under new circumstances. Existing studies have shown that shopping satisfaction consists of two parts, namely, the satisfaction of shopping hedonic value and shopping utilitarian value, and there is a substitution relationship between the two to some extent [8, 9]. Therefore, facing deteriorated accessibility to brick-and-mortar stores (B&MSs), the relocated students must adjust the ratio between the shopping hedonic value and the shopping utilitarian value by changing shopping channels to maintain their QOL with the same amount of shopping expenditure. The most likely way is to increase the number of online shopping times and reduce the number of offline shopping times with the aim of saving travel costs to increase the quantity or quality of purchased goods. Therefore, under the assumption that students' budget constraints, shopping expenditures, and QOL remain unchanged, the impacts of new transport services on students' shopping behaviors are studied, and the changes in shopping transport are assessed in each scenario, as are the corresponding transport-related carbon emissions. The results provide a theoretical basis and technical supports for the innovation of retail sales modes, the exploitation of new transport services, and the optimization of urban transport systems.

Our contributions are as follows:

(1) Integrating the loss of shopping value for online stores or B&MSs into a shopping barrier model
(2) Quantifying the utilitarian shopping value and hedonic shopping value and determining the substitution relationship between the two values
(3) Identifying a real case from which four shopping scenarios with the emergence of new transport services could be derived
(4) Evaluating the impact of shopping behavior and shopping-related transport on carbon emissions based on four shopping scenarios associated with the emergence of two new transport services, namely, TNC and e-commerce and then their logistics.

2. Literature Review

Here, we mainly review the literature on the impacts of new transport services on shopping trips and corresponding emissions, QOL, and shopping values.

To assess the impact of new transport services on shopping trips and corresponding emissions, based on a survey of traditional taxi passengers in Nanjing, Wang et al. [10] divided traditional taxi passengers into three groups according to weekly use, rare use, occasional use, and frequent use and adopted three binary logit models to analyze the behaviors in choosing traditional taxis to find that passengers are more sensitive to positive than to low TNC safety and comfort levels and less sensitive to increased (versus decreased) fare costs. Passengers who occasionally use traditional taxis are more sensitive to comfort than to fare costs. To assess the impact of TNCs on air pollution, Wu et al. [11] constructed an evaluation model composed of three types of TNC services, fuel consumption, and CO_2 emissions to evaluate the impact of TNC trips on energy utilization and CO_2 emissions and found that TNCs have replaced not only private cars but also public transportation (PT), walking, and bicycle use. Under the assumption that the use of PT (including traditional taxis) was not affected by TNC travel in 2015 in China, gasoline consumption increased by approximately 0.25 million tons, resulting in an increase of 0.8 million tons of CO_2 emissions. Sun et al. [12] estimated whole-day roadway NOx emissions by using the Computer Program to Calculate Emissions from Road Transport (COPERT) developed by the European Environment Agency; the input variables were the traffic volume, vehicle type, and running speed, which were extracted from Didi trajectories. Then, roadways were classified according to the 24 hour NO_x emissions based on the temporal fuzzy C-means clustering (FCM) method. A geographical detector and Moran's index were introduced to verify the impact of the built environment on road-source emissions and assess the similarity of emissions generated from nearby road segments. Based on the FCM results, a spatial autoregressive moving average model was used to evaluate the impact of selected built environment factors on roadway emissions; the authors found that NO_x emissions along roadways increased substantially for short road segments, roads near city centers or ramps, roads with many bus stations, and roads close to street blocks with a high proportion of housing or commercial land. Using the positioning data for 7000 traditional taxis and 23,000 Didi vehicles in one month and the corresponding passenger order data, Sui et al. [6] analyzed the fuel consumption and exhaust emissions of TNCs and traditional taxis and found that traditional taxi trips have longer deadhead distances and shorter delivery distances than those for Didi trips. The average deadhead velocity of Didi trips is lower than the delivery velocity. When carrying passengers, fuel consumption, CO_2, NOx, and hydrocarbon emission per kilometer for traditional taxi trips are approximately 1.36, 1.45, 1.36, and 1.44 times those for Didi trips, respectively. Kang et al. [13] estimated the generation of scrap-packing materials, quantified CO_2 emissions from the logistics and transport of parcel deliveries in China from 2007 to 2018, and projected future emissions through 2035 under various scenarios. They found that transport-related CO_2 emissions surged from 0.3 MT in 2007 to 13.7 MT of CO_2 equivalent in 2018, over 80% of which came from online shopping deliveries; these emissions are projected to reach 75 MT of CO_2 equivalent by 2035. Farag et al. [14] assessed the impact of e-commerce on consumers' shopping behaviors and found that every 100 minutes of online shopping can decrease in-store shopping by 20%. Weltevreden et al. [15] conducted a survey to study the potential impacts of online shopping on in-store shopping and found that in-store shopping of consumers decreased due to online shopping. Weltevreden et al. [16] conducted a survey on Internet users to study how their perception of the attractiveness of urban centers affects the relationship between online shopping and in-store shopping and found that due to online shopping, over 20% of consumers reduced the time they spent shopping in downtown stores. Shi et al. [17] discussed the substitution of online shopping for in-store shopping when consumers purchase clothes, footwear, electronic products, food, beverages, and cosmetics and found that due to the availability of online shopping, 44% of the interviewees reduced their in-store shopping trips.

The currently widely accepted definition of QOL proposed by Group [18] describes QOL as individuals' perceptions of their status in their culture and value system, as well as their feelings on their goals, expectations, standards, and living conditions. QOL can be measured, but the measurement indicators used in different studies vary greatly [19]. In the field of medicine, Seo et al. [20] argued that students' QOL is related to their perceived stress, depressive symptoms, and health-promoting lifestyle behaviors. Li et al. [21] contended that students' QOL is related to the severity of mobile phone addiction. Sany et al. [22] employed hierarchical regression and path analysis to examine the relationship between students' QOL and life satisfaction, subjective norms, overall health, optimism, and life attitude. These factors significantly affect students' QOL, and general health status and life satisfaction presented the strongest association with QOL. In the field of urban planning, Cecil et al. [23] proposed that the key elements of the QOL of community residents are living standards, income levels, and access to goods and services. Lee et al. [24] proposed four transport-related QOL dimensions (physical, mental, social, and economic well-being) and argued that they were mainly affected by mobility/accessibility, built environment, and vehicle traffic. Yu et al. [25] explored the importance of elderly friendly rural communities and their impact on the QOL of the elderly and found that the QOL of the elderly is affected by housing, outdoor space, participation in social activities, and PT.

Regarding the shopping value, Babin et al. [26] developed a shopping value measure scale and proved that the shopping value includes two elements, i.e., utilitarian and hedonic. Subsequently, researchers began to study the utilitarian shopping value and hedonic shopping value from different perspectives. Morris et al. [27] investigated the motivation to engage in online shopping from the perspectives of utilitarianism and hedonism to analyze the effects of these dual motives on search intention and purchase intention and found that utilitarian motivation is the determinant of search intention and purchase intention, while hedonic motivation has a direct impact on search intention but an indirect impact on purchase intention. Utilitarian motivation is affected by convenience, cost savings, information availability, and diversified selection, while hedonic motivation is determined by adventure, authority, and status. Wang [28] used a structural equation model to explore whether differences in the hedonic value and utilitarian value affect consumers' information search and shopping intentions on the Internet and found that the perceived hedonic value and utilitarian value have significantly different effects. Hedonic values have a stronger positive association with customer intention to buy than with that of customer intention to search for information. Kim et al. [29] used structural equation modeling to study the impact of the quality of various online shopping websites on the utilitarian shopping value and hedonic shopping value and explored the impact of the perceived level of online shopping value on customer satisfaction and repurchase intention. Kesari et al. [9] also used a structural equation model to study the impact of utilitarian shopping values and hedonic shopping values on shopper satisfaction in Indian shopping centers and found that the two values both have a significant positive impact on customer satisfaction. Chebat et al. [30] investigated the psychological process of the changes in shoppers' consumption behavior caused by renovated shopping malls and discussed the impact of shopping mall renovation on shoppers' consumption, especially the impact of shoppers' perception of shopping mall atmosphere. They found that the hedonic value contributes more than the utilitarian value to shopper satisfaction. The utilitarian value will affect shoppers' spending, while the hedonic value will not. Ercan et al. [31] examined how hedonic and utilitarian values relate to tourists' overall shopping experience satisfaction and destination loyalty and found that the hedonic value and utilitarian value are closely related to overall shopping satisfaction. Overall shopping satisfaction fully mediates the effect of utilitarian shopping value on destination repatronage intention and destination word-of-mouth and partially mediates the effect of hedonic shopping value on destination repatronage intention and destination word-of-mouth.

In summary, TNC and e-commerce affect not only consumers' shopping choices but also the carbon emitted from shopping-related transportation. Most existing studies have focused on the impact of a single new service on personal shopping behavior or emissions and have rarely focused on the impacts of multiple new transport services. However, the literature on QOL and shopping value does not clearly illustrate their relationships.

3. Model Construction

3.1. Problem Description. Differences in the availability of new transport services for passengers and commodities can be observed in various regions or cities in different growth stages, while multiple new transport services are not available simultaneously in many cities. Therefore, as mentioned above, based on real cases, we establish four scenarios for analyzing consumers' shopping behaviors and calculate the carbon emissions of shopping-related transport corresponding to different availabilities of new transport services. The reason why university students' shopping is considered the research focus is because the students in our campus have experienced shopping scenarios (1) and (2), while the other two shopping scenarios ((3) and (4)) could be deduced from scenarios (1) and (2) according to logic. This campus is the newly opened Meishan campus of Ningbo University (China), which is approximately 50 km from the main campus and central business district (CBD) of the city. The new campus began its operation in July 2018. Over 3000 students in two colleges of Ningbo University were relocated to study and live on the new campus in September 2018. Meishan is a newly developed urban area with few living facilities within 10 km. During the period from September to December 2018, due to a lack of retail infrastructure, the students mainly relied on e-commerce to purchase commodities. E-commerce with an information platform can cover remote areas with little additional cost, and the purchased commodities are delivered in a centralized manner, which is helpful for students to save shopping costs. Therefore, new commodity transport services existed immediately following the relocation. However, due to the lack of travel demand because of high travel costs, it was difficult for TNC services to obtain round-trip requests. Thus, it can be considered that TNC services were not available at that time, and students would not have received a response after placing orders. Therefore, the students had access to new commodity transport services but no new passenger transport services (scenario (1)) were seen from September to December 2018. Subsequently, from January to August 2019, due to continuous market cultivation, the response time of TNC became increasingly shorter. By September 2019, new passenger transport services (mainly Didi Travel) were popularized on the new campus. Therefore, during the period from September to December 2019, the students had both a new commodity transport service and a new passenger transport service (scenario (2)).

When students moved to the new campus in a remote area, e-commerce had already been popularized, and it was difficult to find a case without new commodity transport or passenger transport services (scenario (3)) or without new commodity transport services but with new passenger transport services (scenario (4)). However, theoretically, there is a substitutive relationship between online and offline shopping [7, 17, 32–34]; therefore, under the assumption that personal total expenditures for shopping remained unchanged, the shopping data for scenario (3) and scenario (4) can be deduced from the shopping data for scenario (2) and scenario (1), respectively. The definition of each scenario and description of the data used are shown in Table 1.

Therefore, based on the four shopping scenarios and the assumption that students' personal total shopping expenditures and QOL remained unchanged, their choices of shopping channels, brick-and-mortar stores, and shopping travel modes are modeled based on surveyed shopping data. Then, the QOL model is calibrated based on the predicted shopping choices. Finally, the number of online and offline shopping sessions is estimated for the four scenarios, and the impact of new transport services on student shopping behaviors and the changes in the transport demand and corresponding emissions are analyzed. The detailed model flow is shown in Figure 1.

3.2. Data Description

3.2.1. Study Area. As discussed above, we study the behaviors of students at Ningbo University who had lived on the main campus for two years (September 2016 to August 2018) and the subcampus for the remaining two years (2018.9–2020.8). The main campus is located in the central city, while the Meishan subcampus is located 50 km from the central city and opened in July 2018. The main commercial areas for the students living on the Meishan subcampus are the nearby commercial street, i.e., Chunxiao CBD, and Yintai Plaza. Figure 2 shows the situation.

To perform the numerical analysis, we collected students' shopping activity data for the periods of September–December 2018 and September–December 2019 and used the data to establish scenarios (1) and (2), respectively. Then, data for scenarios (3) and (4) were deduced accordingly. The survey work is described as follows.

3.2.2. Questionnaire Distribution and Collection. Our team has performed a series of studies of students' shopping behaviors. We conducted a follow-up survey of the sampled students and published some research based on the survey analysis. In previous surveys, we obtained data about students' online and offline purchases during September–December 2018. To obtain the shopping data of students during September–December 2019, we continued the follow-up survey. For this survey, in a classroom on the Meishan campus, our team members interviewed students who were

Table 1: Definition of each scenario and description of the data used for each scenario.

Scenario	Definition	Description of data
(1)	With new commodity transport services but without new passenger transport services	Shopping data from Sepember. to December 2018, such as number of shopping sessions
(2)	With both new commodity transport services and new passenger transport services	Shopping data from September to December 2019, such as number of shopping sessions
(3)	Without new commodity transport or a passenger transport services	Deduced from scenario 2
(4)	Without new commodity transport services but with new passenger transport services	Deduced from scenario 1

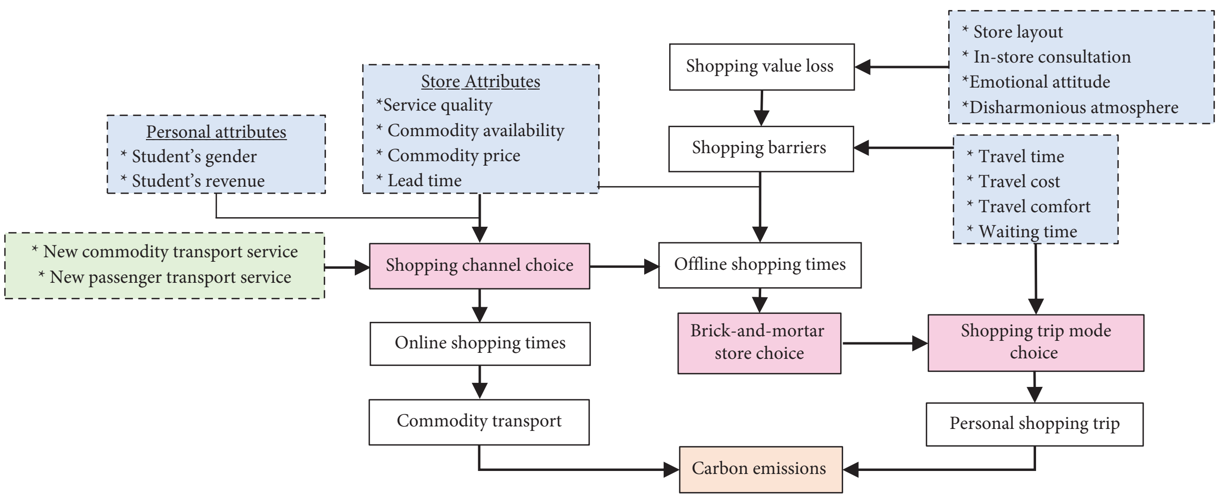

Figure 1: The model structure.

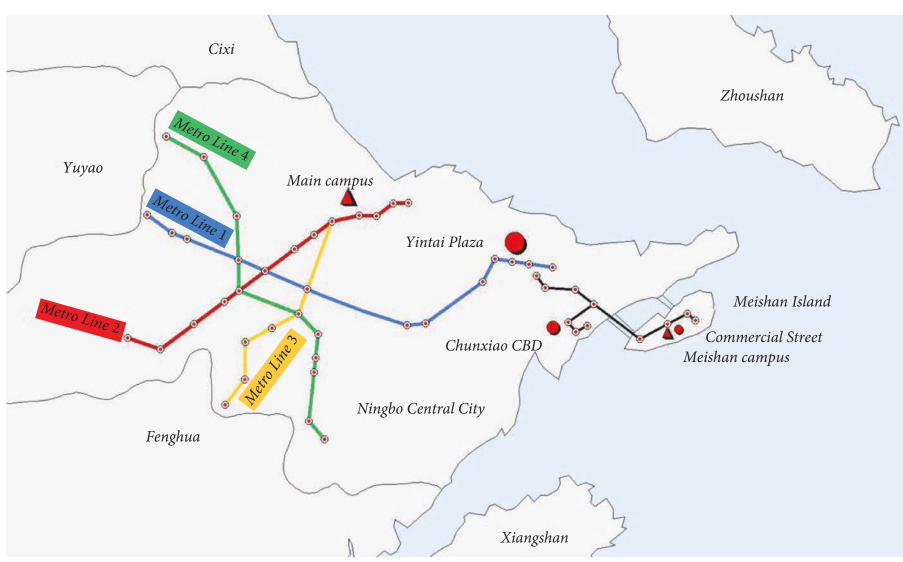

Figure 2: Location of Ningbo university.

willing to continue the follow-up survey. During the interviews, our team members asked interviewees to log into their online shopping accounts and then used crawler technology to collect the online shopping data (such as names, prices, and quantities of the commodities purchased online) from September to December 2019. The interviewee wrote the answers for the questions on the questionnaire sheets.

We employed the methods in Sun et al. [35] and Yang et al. [7] to determine the factors affecting shopping mode choices, B&MS choices, and shopping satisfaction. Moreover, based on Gao et al. [8], shopping value factors are selected. Furthermore, we used a 10-point Likert scale [36] to measure the commodity availability and service quality of stores among the identified driving factors and had the students score the commodity availability and service quality of stores from high to low (from 10 to 0) based on their experience.

The specific survey contents are shown in Table 2, and the questionnaire sheet is provided inthe section Supplementary Materials. Our team members conducted face-to-face interviews with students who were willing to be involved. The overall male-to-female ratio of the students at Ningbo University is 4 : 6. To ensure the usefulness of the trained model, the male-to-female ratio in the surveyed data should also be 4 : 6. Therefore, of the 150 students whom we surveyed, 38% were male and 62% were female, that is consistent with the overall male-to-female ratio of the students. For ease of understanding, explanations of the variables and parameters are listed in Table 3.

3.3. Shopping Choice Model. Overall, students must make three shopping choices: a shopping channel choice, a brick-and-mortar store choice, and a travel mode choice. The corresponding decision-making models are described as follows.

3.3.1. Shopping Channel Choice. Currently, consumers can purchase commodities through both online and offline channels. Students' shopping channel choices are affected by several factors, and their decision-making is highly random and uncertain, making it difficult for us to accurately devise a function to depict the relationship between shopping channel choices and their drivers due to data availability. A back-propagation (BP) neural network has a strong mapping ability and high self-learning and self-adaptive ability with a set of training data to determine an approximate relationship through iterative learning without human intervention [37]. Therefore, to analyze consumers' choices regarding shopping channels, a BP neural network model is adopted, and its structure is shown in Figure 3.

3.3.2. Brick-and-Mortar Store Choice. The total attractiveness of a B&MS is determined by the attractiveness of its multiple attributes. Therefore, the weighted sum of the attractiveness values of all of the attributes of a B&MS could be considered the total charm value of a B&MS, which can be calculated as

$$Y_{nj} = \sum_{k=1}^{K} \delta_k y_{kj}, \tag{1}$$

where Y_{nj} is the total attractiveness (indicated by the service level, quality of commodities, and average price of commodities, among other factors) of B&MS j; y_{kj} is the kth attractiveness index for B&MS j; and δ_k is the weight of the kth index. Based on the gravity model, consumers' store choice utility is directly proportional to the store's total attractiveness and inversely proportional to shopping barriers, which is given as

$$U_{\mathrm{nij}} = \frac{Y_{\mathrm{nj}}}{H_{\mathrm{nij}}}, \tag{2}$$

where H_{nij} is the shopping barrier for B&MS j; U_{nij} is the B&MS choice utility of consumer n in scenario i; and the B&MS choices model is built to estimate consumers' B&MS choice probabilities as

$$P_{nij} = \frac{U_{nij}}{\sum_{j=1}^{J} U_{nij}}. \tag{3}$$

P_{nij} is the probability of student n shopping at B&MS j in scenario i.

3.3.3. Shopping Trip Mode Choice. To analyze travel mode choices when the students go shopping in B&MSs, the following discrete choice model is used:

$$U_{nm} = \sum_{l=1}^{L} \omega_l x_{nml} + \varepsilon_{nm}, \tag{4}$$

$$P_{nijm} = \frac{e^{U_{nm}}}{\sum_{m' \in M_{ij}} e^{U_{nm'}}}, \tag{5}$$

where U_{nm} is the utility of student n choosing mode m, and x_{nml} is the lth factor that influences the travel utility of student n choosing mode m (such as the travel time, travel cost, comfort level, or waiting time); ε_{nm} is the unobservable part of utility, which is a random error term; M_{ij} denotes the alternative travel modes that can be chosen to go shopping at B&MS j in scenario i; and P_{nijm} is the probability that student n chooses travel mode m to shop at B&MS j in scenario i.

3.4. Calculation of Shopping Expenditures. The total student expenditure for shopping include the money spent on online purchases, the money spent on offline purchases, and the money used for shopping travel, and it can be expressed as follows:

$$\begin{aligned} L_{ni} &= x_{ie} X_{ni0} L_{ni0} + \sum_{j=1}^{J} X_{nij} L_{nij} + 2 \sum_{j=1}^{J} \sum_{m=1}^{M_{ij}} X_{nij} P_{nijm} C_m D_j, \\ &\cdot \begin{cases} m_{\mathrm{new}} \in M_{ij}, x_{id} = 1 \\ m_{\mathrm{new}} \notin M_{ij}, x_{id} = 0 \end{cases}, \\ X_{nij} &= X_{niS} P_{nij}, j >= 1, \\ x_{ie} &= \begin{cases} 0, \text{without new commodity transport service in scenario } i \\ 1, \text{with new commodity transport service in scenario } i \end{cases}, \end{aligned} \tag{6}$$

where L_{ni} is the total shopping expenditures of student n in scenario i ($i = 1, 2, 3, 4$). The first term on the right-hand side of the equation is the money spent purchasing commodities

Table 2: Main survey contents.

Variable	Survey content
Attributes of travel mode	(i) Travel time (ii) Travel cost (iii) Comfort (iv) Waiting time
Store attributes	(i) Commodity availability (ii) Service quality (iii) Commodity price
Shopping satisfaction	(i) Satisfaction with shopping accessibility (ii) Satisfaction with service quality (iii) Satisfaction with commodity availability (iv) Satisfaction with commodity price
Factors affecting shopping value	(i) Store layout (ii) In-store consultation (iii) Emotional attitude toward store (iv) Disharmonious shopping atmosphere in-store
Personal characteristics	Monthly living expenses in scenarios (1) and (2)
Attributes of online shopping	(i) The type of commodities purchased online in scenarios (1) and (2) (ii) Number of times various commodities were purchased online in scenarios (1) and (2) (iii) Time for online shopping (browsing time and payment time) in scenarios (1) and (2)
Attributes of offline shopping	(i) Number of offline shopping instances in scenarios (1) and (2)

Table 3: Nomenclature of variables/parameters.

Variables/ Parameters	Definition/Explanation
x_{id}	A binary variable (the set of alternative modes M_{ij} containing new passenger transport service m_{new}, $x_{id}=1$; otherwise, $x_{id}=0$)
x_{ie}	A binary variable (with new commodity transport service in scenario i, $x_{ie}=1$; otherwise, $x_{ie}=0$)
δ_k	The weight of the kth index (such as the service level, quality of commodities, and average price of commodities)
w_i	The lth factor that influences the travel utility of student n choosing mode m (such as the travel time, travel cost, comfort level, or waiting time)
β_{i1}	Satisfaction with shopping accessibility in scenario i
β_{i2}	Satisfaction with service quality in scenario i
β_{i3}	Satisfaction with commodity availability in scenario i
β_{i4}	Satisfaction with commodity price in scenario i
τ_{ni}	The number of purchases in scenario i
η_{ni}	Shopping barriers in scenario i
α_{i1}	Gap due to store layout in scenario i
α_{i2}	Gap due to in-store consultation in scenario i
α_{i3}	Gap due to emotional attitude toward a store in scenario i
α_{i4}	Gap due to disharmonious shopping atmosphere in a store in scenario i
γ_{i1}	Satisfaction with shopping on nearby commercial streets in scenario i
γ_{i2}	Satisfaction with shopping in the Chunxiao CBD in scenario i
γ_{i3}	Satisfaction with shopping in Yintai Plaza in scenario i
δ_i	Online shopping satisfaction in scenario i

online, where X_{ni0} is the number of online orders for student n, and L_{ni0} is the average expenditures for one online shopping session for student n (unit: *CNY*). The latter variable equals the average price of all commodities purchased online. The price of online sales includes the price of the commodity itself and the cost of commodity delivery. The second term is the money spent purchasing offline commodities, where X_{nij} is the number of times student n shops in B&MS j in scenario i, X_{niS} is the total number of shopping trips for student n under scenario i, and L_{nij} is the one-time average expenditure of student n shopping in B&MS j (unit: CNY). The third term is the payment for travel services, C_m is the unit price of travel services for mode m, and D_j is the shopping trip distance. X_{id} is a binary variable (the set of alternative modes M_{ij} containing new passenger transport service m_{new}, $x_{id}=1$; otherwise, $x_{id}=0$).

3.5. QOL Measurement. QOL is influenced by several factors, but in China, university students living on the campuses basically rely on their parents' financial support. Beyond purchasing commodities and services, students rarely need to go off campus; therefore, their QOL mainly depends on their satisfaction with purchasing commodities and services, as has been reported in the previous research

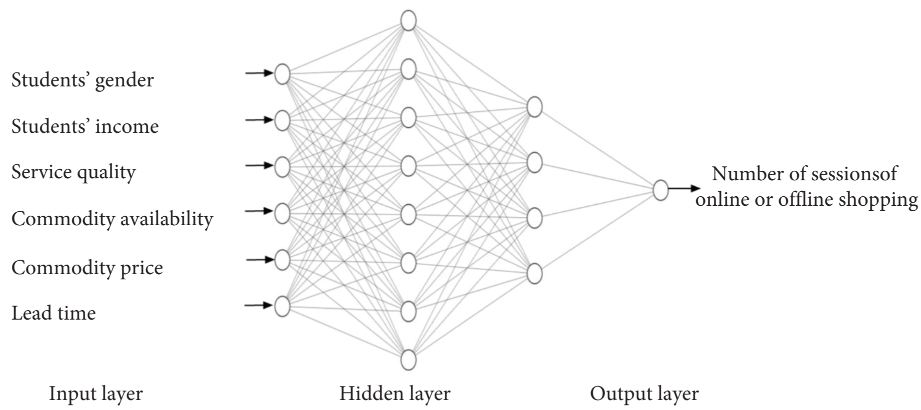

Figure 3: Structure of the BP neural network model.

[7]. Obviously, new transport services (e-commerce, commodity delivery, and TNC) do not affect other QOL factors beyond commodity and service purchases. Therefore, we consider only the influence of shopping-related factors on QOL and assume that the other factors do not change. Thus, we can use the changes in student satisfaction with commodity (or service) purchases to measure QOL.

Due to "Internet +," students can buy commodities both online and offline. Therefore, QOL should include two parts: online shopping satisfaction and offline shopping satisfaction. The Cobb–Douglas production function is a typical nonlinear method that is used to calculate the production value based on the inputs of labor, capital, and land. The mechanism by which total shopping satisfaction derives from the satisfaction with both online shopping and offline shopping fits the Cobb–Douglas production function well; therefore, we use the Cobb–Douglas production function to estimate shopping satisfaction as follows:

$$Q_{ni} = Q_{ni0}^{x_{ie}\lambda_i} Q_{niS}^{\left(1-x_{ie}\lambda_i\right)}, \tag{7}$$

where Q_{ni} is the shopping satisfaction of student n in scenario i; Q_{ni0} and Q_{niS} are the satisfaction levels for online shopping and offline shopping, respectively, and λ_i ([0, 1]) is a parameter. Offline shopping satisfaction is determined by a student's satisfaction with visited B&MSs and is expressed as follows:

$$Q_{niS} = \prod_{j=1}^{J} Q_{nij}^{\psi_{ij}}, \tag{8}$$

where Q_{nij} is student n's satisfaction with shopping in B&MS j, which is scored from high to low (10 to 0) by the student. ψ_{ij} ($\sum_{j=1}^{J} \psi_{ij} = 1$) is a parameter. This satisfaction is usually determined by transport accessibility, service quality, the types and quantities of commodities, and prices in B&MSs [38], and this relationship can be formulated as follows:

$$Q_{nij} = \beta_{i1} A_{nij} + \beta_{i2} S_{nij} + \beta_{i3} T_{nij} + \beta_{i4} R_{nij} + \theta_i, \tag{9}$$

where A_{nij} ($j = 0$: online store, $j \geq 1$: B&MS) is the accessibility for student n traveling to store j in scenario i. Additionally, S_{nij}, T_{nij}, and R_{nij} are student n's satisfaction with shopping services, commodity availability, and the prices of commodities in store j under scenario i, respectively; β_{i1}, β_{i2}, β_{i3}, and β_{i4} are the accessibility parameter for student n traveling to store j, student n's satisfaction with shopping services, commodity availability, and the prices of commodities in store j under scenario i, respectively; and θ_i is the constant term under scenario i.

3.6. Calculation of Shopping Accessibility. Accessibility is mainly defined along three dimensions: the potential of opportunities for interaction [39], the ease with which a site can be reached, or the ease with which an activity can be participated in using a transport mode [40, 41]; and the combination of site convenience based on a transport system and the quality/quantity of opportunities is offered at the site [42, 43]. Based on the second model, the model of shopping accessibility is built as follows:

$$A_{nij} = \frac{X_{nij}^{\tau_{ni}}}{H_{nij}^{\eta_{ni}}}, \tag{10}$$

where τ_{ni} and η_{ni} are parameters.

3.7. Calculation of Shopping Barriers. Shopping barriers usually refer to the spatial barriers that consumers need to overcome when shopping in B&MS and is generally expressed by a generalized travel cost. In addition, theoretically, when consumers buy commodities in B&MS, the gap between satisfaction levels for an ideal and a real store will reduce a consumer's sense of pleasure. A gap greater than 0 reflects consumer unhappiness from offline shopping, and a gap smaller than 0 reflects consumer happiness during shopping [44–46]. The weighted sum of the satisfaction gaps from a set of store attributes is defined as the shopping value loss and can be converted into a monetary term. The shopping value is the combination of utility-based feelings regarding purchased commodities and satisfaction from the shopping experience in B&MSs, which are called the utilitarian value and hedonic value, respectively [26, 47–49]. The utilitarian value is reflected in utility-based feelings related to commodities after shopping [26] because the use function of a commodity does not change based on the method with which the commodity is obtained. The utilitarian value rarely exhibits value loss. The hedonic shopping value comes from experienced happiness during shopping [26], which is affected by a store's attributes. For different shopping channels and shopping sites, consumers may perceive different hedonic shopping values, and thus, their losses are also different [50]. Therefore, based on the spatial barriers that need to be overcome and the loss of hedonic value that may occur during shopping, shopping barriers are estimated as follows:

$$H_{nij} = F_{nij} + V_{nij-L},$$
$$F_{nij} = \begin{cases} \dfrac{\sum_{m=1}^{M_{ij}} P_{nijm}\left(C_{ijm} + \mu_1 T_{ijm} + \mu_2 W_{ijm}\right), \quad j> = 1}{\mu\left(T_E + T_B + T_O\right), \quad j = 0} \end{cases},$$
$$V_{nij-L} = \sum_{k=1}^{K} \alpha_{ik}\left(X_{ijk} - x_{ijk}\right) + \vartheta_i, \tag{11}$$

where F_{nij} is the spatial barrier that must be overcome; V_{nij-L} is the hedonic value loss perceived by student n when shopping in B&MS j in scenario i; M_{ij} is the alternative set of travel modes when shopping in B&MS j; C_{ijm} is the money paid by students when choosing travel mode m for B&MS j; T_{ijm} is the travel time; and W_{ijm} is the waiting time. μ_1 and μ_2 are the time value of T_{ijm} and W_{ijm}, respectively. Based on Yap et al's study [51], we set $\mu_2 = 1.55\mu_1$. T_E and T_B are the average times for ordering and browsing for online commodities, respectively; T_O is the average lead time of orders; and μ is the time value. X_{ijk} is the expected value of attribute k for ideal store j (the ideal value is set to 100 CNY); and x_{ijk} is factor k for store j, which affects the loss of hedonic value and is mainly related to a store's atmosphere, in-store consultation, the consumer's emotional attitude (consumer's cognition of the store and internal emotional reactions), and store layout [8]. The scores for these factors can be converted into monetary values ranging from 0 to 200 CNY. Finally, α_{ik} is a parameter, and ϑ_i is the constant term under scenario i.

3.8. Model of Emissions from Delivery Vehicles. The carbon emissions for shopping-related transport, such as trips involving delivery trucks, PT vehicles, traditional taxis or TNC vehicles, private cars, and bicycles and walking, are considered under the assumption that walking and bicycles are zero-emission modes. According to a 2006 IPCC report [52], the emissions from fuel-based traditional taxis are as follows:

$$\mathrm{NC}_{i-oil} = \sum_{n=1}^{N}\sum_{j=1}^{J} f_{nij1} D_j O \rho \mathrm{HF}, \tag{12}$$
$$f_{nij1} = X_{nij} P_{nij1},$$

where $\mathrm{NC}_{\text{i-oil}}$ is the CO_2 emissions (unit: kg) for a fuel-based traditional taxi vehicle in scenario i; f_{nij1} is the number of times that student n uses fossil conventional taxi vehicles for shopping at B&MS j in scenario i; D_j is the running distance of the traditional taxi vehicle (unit: km); O is the traditional taxi vehicle's fuel consumption per kilometer (unit: L/km); ρ is the fuel density (unit: kg/L) of fossil conventional taxi vehicles; and H and F are the net calorific value of the fuel (unit: MJ/kg) and the CO_2 emissions factor for the fuel (unit: kg/MJ), respectively. The relocation of the campus has broken the equilibrium of the supply and demand regarding local bus services. To keep the supply with the changed demand, the bus company must increase the supply of bus services. Under the assumption that the added bus vehicles serve the new increased demand caused by the students, the carbon emissions of bus trips per student are calculated according to the bus vehicle's capacity as follows:

$$\mathrm{NC}_{i-\mathrm{power}} = \sum_{n=1}^{N}\sum_{j=1}^{J} f_{nij2} \cdot \frac{D_j E_2 F_2}{\mathrm{Num}}, \tag{13}$$
$$f_{nij2} = X_{nij} P_{nij2},$$

where $\mathrm{NC}_{\text{i-power}}$ is the CO_2 emissions (unit: kg) for an electric bus; f_{nij2} is the number of times that student n rides electric buses for shopping at B&MS j in scenario i; E_2 is the average power consumed by the electric buses (unit: kW·h/km); F_2 is the CO_2 emissions coefficient (unit: kg/(kW·h)); and Num is the maximum capacity of an electric bus. The calculation of the amount of carbon emitted by delivery trucks is as follows:

$$\mathrm{NC}_{i-\mathrm{diesel}}\left(F_{\mathrm{tra}}\right) = \sum_{j=1}^{J} f_{ni0} D_{j0} O_0\left(F_{\mathrm{tra}}\right) \rho_0 H_0 F_0,$$
$$f_{ni0} = \sum_{n=1}^{N} \frac{X_{ni0}}{G\left(F_{tra}\right)}, \tag{14}$$
$$O_0\left(F_{\mathrm{tra}}\right) = \frac{c \cdot \left(F_{tra} - a\right) + b_1}{100},$$

where $\mathrm{NC}_{\text{i-diesel}}$ (F_{tra}) is the CO_2 (unit: kg) emitted by trucks during delivery; f_{ni0} is the number of trucks; D_{j0} is the delivery distance of the trucks (unit: km); and O_0 (F_{tra}) is the average fuel consumed by a truck (unit: L/km), which is related to the total weight of the truck F_{tra}. C is the variation coefficient for fuel consumption with the total weight of a truck; a is the weight of an empty truck; and b_1 is a constant. The values of c, a, and b_1 are 0.64, 15, and 23.3 [53], respectively. ρ_0 is the density of diesel; H_0 is the net calorific value of diesel (unit: MJ/kg); F_0 is the CO_2 emission factor for diesel (unit: kg/MJ); and G (F_{tra}) is the average number of commodities carried in one delivery by truck with a maximum load of F_{tra} and is an empirical constant.

3.9. Model of Emissions from Retail Commodity Distribution. The retail commodity distribution network in a real city is depicted in Figure 4, where the solid lines and dotted lines represent logistical activities and information flows, respectively; additionally, the red lines represent online shopping activities, and the black lines represent offline shopping activities.

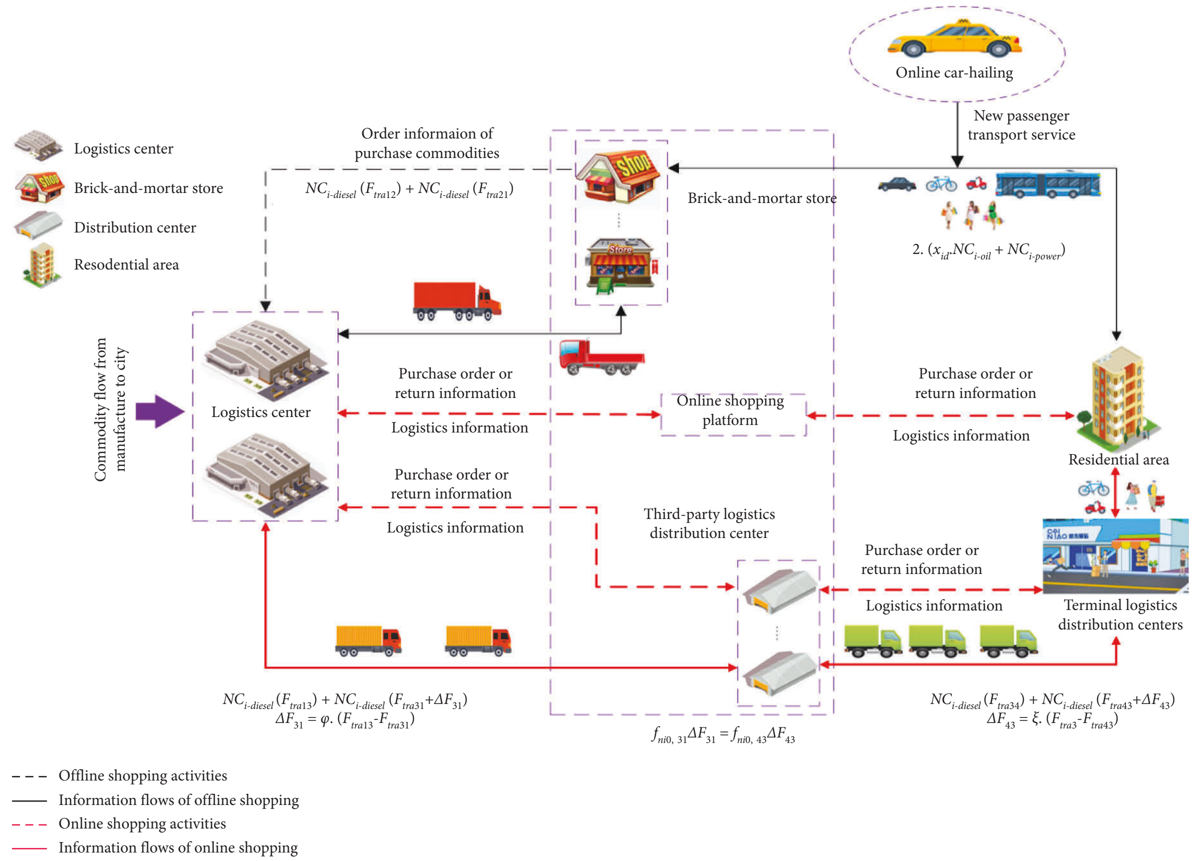

Figure 4: Retail commodity distribution network in cities.

Transport for the circulation and distribution of retail commodities includes the transport of commodities from logistics centers (LCs) to B&MSs by truck, the empty return trips of trucks from B&MSs to LCs, consumers' personal trips from their homes to B&MSs and back home, the transport of retail commodities by truck from LCs to distribution centers (DCs), the delivery trips for trucks from DCs to terminal logistics DCs (TLDCs), consumers' personal trips from their homes to TLDCs and back home, and the transport of returned commodities by truck from TLDCs to DCs or from DCs back to LCs. In the case of the university campus, TLDC is very close to students' dormitories. Students usually walk or ride bicycles to TLDC to retrieve or return goods. The carbon emissions generated by this travel could be neglected. Therefore, for calculating carbon emissions, the last-mile delivery is not considered. The carbon emitted from shopping-related transport in different scenarios can be calculated as follows:

$$
\begin{aligned}
\mathrm{NC}_{i,\mathrm{total}} &= \mathrm{NC}_i \cdot \mathrm{Pop},\\
\mathrm{NC}_i &= \left\{\mathrm{NC}_{i-\mathrm{diesel}}\left(F_{\mathrm{tra}12}\right) + \mathrm{NC}_{i-di\ esel}\left(F_{\mathrm{tra}21}\right)\right\} + \left\{2\cdot\left(x_{\mathrm{id}}\cdot \mathrm{NC}_{i-\mathrm{oil}} + \mathrm{NC}_{i-\mathrm{power}}\right)\right\}\\
&\quad + \left\{x_{\mathrm{ie}}\cdot\left(\mathrm{NC}_{i-\mathrm{diesel}}\left(F_{\mathrm{tra}13}\right) + \mathrm{NC}_{i-\mathrm{diesel}}\left(F_{\mathrm{tra}31} + \Delta F_{31}\right)\right\}\right.\\
&\quad + \left\{x_{\mathrm{ie}}\cdot\left(\mathrm{NC}_{i-\mathrm{diesel}}\left(F_{tra34}\right) + \mathrm{NC}_{i-\mathrm{diesel}}\left(F_{\mathrm{tra}43} + \Delta F_{43}\right)\right)\right\},\\
\Delta F_{31} &= \phi\cdot\left(F_{\mathrm{tra}13} - F_{\mathrm{tra}31}\right),\\
\Delta F_{43} &= \xi\cdot\left(F_{\mathrm{tra}34} - F_{\mathrm{tra}43}\right),\\
f_{\mathrm{ni}0,31}\Delta F_{31} &= f_{\mathrm{ni}0,43}\Delta F_{43},
\end{aligned}
\tag{15}
$$

where $\mathrm{NC}_{\mathrm{i,total}}$ is the total carbon emissions due to shopping on the whole campus in scenario *i*. *Pop* is the total number of students on the whole campus. NC_i is the carbon emissions from monthly per capita shopping-related transportation in scenario *i*. The first term on the right side of Eq. (15) is the carbon emitted from trucks transporting commodities from LCs to B&MSs and then returning to LCs, where $\mathrm{NC}_{\mathrm{i\text{-}diesel}}$ (F_{tra12}) and $\mathrm{NC}_{\mathrm{i\text{-}diesel}}$ (F_{tra21}) are the carbon emitted from

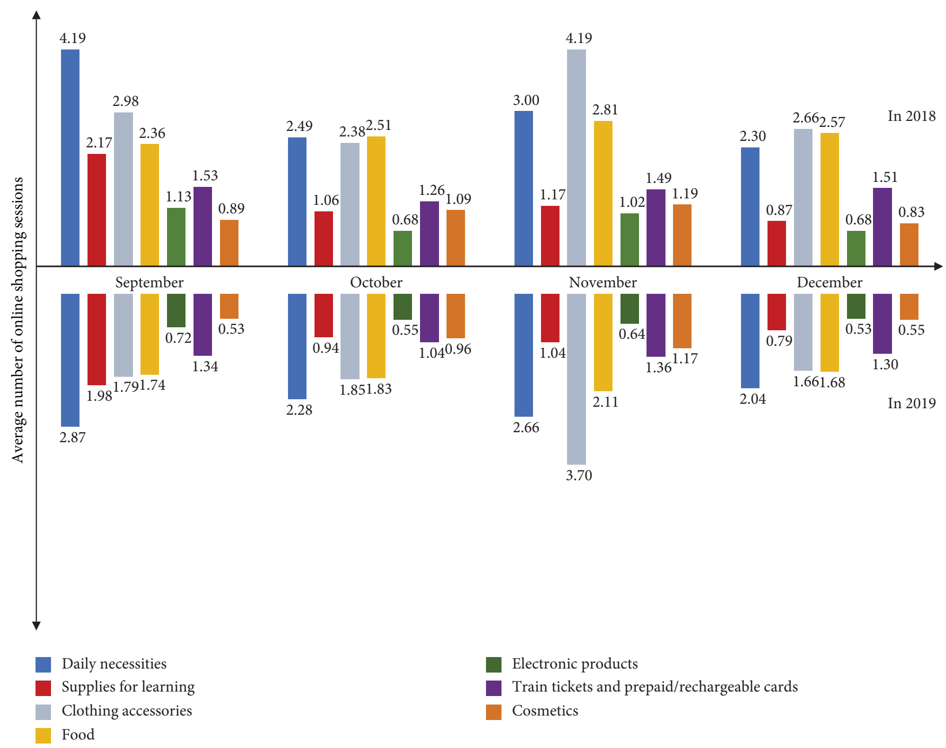

Figure 5: The various commodities purchased online.

trucks with loads from LCs to B&MSs and empty trucks traveling from B&MSs to LCs, respectively. $F_{\mathrm{tra}12}$ and $F_{\mathrm{tra}21}$ are the total weights of the trucks with loads from LCs to B&MSs and the weights of the empty trucks, respectively. The second term is the carbon emitted from consumers' personal trips for shopping at B&MSs and transporting commodities back to their homes. The third term is the carbon emitted from trucks transporting commodities purchased online from LCs to DCs and the trips back to LCs, where $\mathrm{NC}_{\text{i-diesel}}\,(F_{\mathrm{tra}13})$ and $\mathrm{NC}_{\text{i-diesel}}\,(F_{\mathrm{tra}31} + \Delta F_{31})$ are the carbon emitted from trucks transporting commodities from LCs to DCs and returning to LCs, respectively. $F_{\mathrm{tra}13}$ and $F_{\mathrm{tra}31}$ are the total weight of trucks carrying loads from LCs to DCs and the weight of empty trucks, respectively. ΔF_{31} is the weight of a truck transporting returned commodities from DCs to LCs. The fourth term is the carbon emitted from the round trips of trucks transporting commodities sold online from DCs to consumers and returning to DCs, where $\mathrm{NC}_{\text{i-diesel}}\,(F_{\mathrm{tra}34})$ and $\mathrm{NC}_{\text{i-diesel}}\,(F_{\mathrm{tra}43} + \Delta F_{43})$ are the carbon emitted from trucks transporting commodities from DCs to consumers' homes and returning to DCs, respectively. $F_{\mathrm{tra}34}$ and $F_{\mathrm{tra}43}$ are the total weight of trucks carrying loads from DCs to consumers' homes and the total weight of the empty trucks, respectively. ΔF_{43} is the weight of trucks transporting returned commodities from consumers' homes to DCs. φ and ξ are the ratio of the weight of returned commodities transported by trucks from DCs to LCs to the weight of commodities transported by trucks from LCs to DCs and the ratio of the weight of returned commodities transported by trucks from consumers' homes to DCs to the weight of the commodities transported by trucks from DCs to consumers' homes. $f_{ni0,\,31}$ and $f_{ni0,\,43}$ are the number of trucks from DCs to LCs and from consumers' homes to DCs, respectively.

4. Shopping Data Analysis

Based on online buying data, purchased commodities are divided into seven categories [17, 35]: daily necessities, school supplies, clothing accessories, food, electronic products, train tickets and prepaid/rechargeable cards, and cosmetics. In the statistical analysis, one payment for an online purchase was regarded as one instance of online shopping. The online purchase data are shown in Figure 5.

The monthly average number of online shopping sessions in 2018 was larger than that in 2019, which suggests that the students tended to shop online in the early stage of relocation. In September, most purchases were daily necessities, school supplies, and electronic products. September was the beginning of the new semester. In November, most purchases were clothing accessories, food, and cosmetics due to the "Double 11" shopping festival (Chinese e-commerce event). From September to December 2018 and September to December 2019, the numbers of railway tickets and train tickets and prepaid/rechargeable cards purchased were relatively stable, indicating that almost all these kinds of commodities were purchased online.

As shown in Figure 6, from September to December 2018, the monthly average number of online shopping sessions was larger than that in 2019. Notably, 2018 was the initial year of relocation, and PT, Didi Travel, and traditional taxi services were relatively poor. The accessibility of surrounding commercial districts was also poor. To meet their shopping demands, the students were willing to shop online.

Figure 6: The average number of online and offline purchases.

From September to December 2019, the monthly average number of shopping trips was larger than that in 2018. Didi Travel gradually became popular among students, and due to the improvement in shopping accessibility, shopping in B&MSs increased.

5. Numerical Analysis

5.1. Training of the Channel Choice Model. With the normalized survey data, the MATLAB2014a toolbox was used to train the BP neural network for the four scenarios. The best network structure based on the data characteristics was obtained (see Figures 7–10).

Figures 7–10 show that all of the correlation coefficients (Rs) between the predicted (Y-axis) and actual values (X-axis) approached 1, indicating that the accuracy of the trained neural network model was good and that the model could be used to forecast the number of online shopping and offline shopping instances.

5.2. Calibration of the Mode Utility Function. Based on the answers for questions 9–14, Equation (4) was calibrated to obtain Table 4.

The coefficients for the travel time, travel cost, and waiting time are negative, which indicates that they are negatively related to mode utility. The absolute values of the coefficients of the travel cost, travel time, and waiting time increase in turn. The coefficient of comfort is positive, which indicates that this factor is positively correlated with utility, and students will choose high-comfort shopping modes.

5.3. Calibration of the Satisfaction Function. By substituting (8) into (7) and taking the logarithm on both sides of (7), we obtain

$$\ln \mathrm{Q_{ni}} = \delta_i \ln \mathrm{Q_{ni0}} + \sum_{j=1}^{J} \gamma_{ij} \ln \mathrm{Q}_{nij}, \tag{16}$$

where to simplify the expression of the logarithmic equation, we set $\delta_i = x_{ie}\lambda_i$, $\gamma_{ij} = (1 - x_{ie}\lambda_i)\psi_{ij}$, $i \in I$, $j \in J$, and $k \in K$. By substituting equations (9)– (11) into (16), we obtain

$$\begin{aligned} LnQ_{ni} = {} & \delta_i Ln\left[\frac{\beta_{i1} X_{ni0}^{\tau_{ni}}}{\left(\mu\left(T_E + T_B + T_O\right) + \sum_{k=1}^{K} \alpha_{ik} x_{i0k} + \vartheta_i\right)^{\eta_{ni}}} + \beta_{i2} S_{ni0} + \beta_{i3} T_{ni0} + \beta_{i4} R_{ni0} + \theta_i\right] \\ & + \sum_{j=1}^{J} \gamma_{ij} Ln\left[\frac{\beta_{i1} X_{nij}^{\tau_{ni}}}{\left(\sum_{m=1}^{M_{ij}} P_{nijm}\left(C_{ijm} + \mu_1 T_{ijm} + \mu_2 W_{ijm}\right) + \sum_{k=1}^{K} \alpha_{ik} x_{ijk} + \vartheta_i\right)^{\eta_{ni}}} + \beta_{i2} S_{nij} + \beta_{i3} T_{nij} + \beta_{i4} R_{nij} + \theta_i\right], \end{aligned} \tag{17}$$

where δ_i, α_{ik}, ϑ_i, τ_{ni}, η_{ni}, β_{i1}, β_{i2}, β_{i3}, β_{i4}, θ_i, and γ_{ij} are parameters. In this study, the least-squares method and genetic algorithm are used for calibration. The crossover rate and mutation rate are set to 0.6 and 0.01, respectively [54, 55]. The fitness values in the four scenarios tend to stabilize after 70 iterations (Figure 11). To obtain the optimal value, the output after 120 iterations is used as the final result. The optimal parameters for the four scenarios are shown in Table 5.

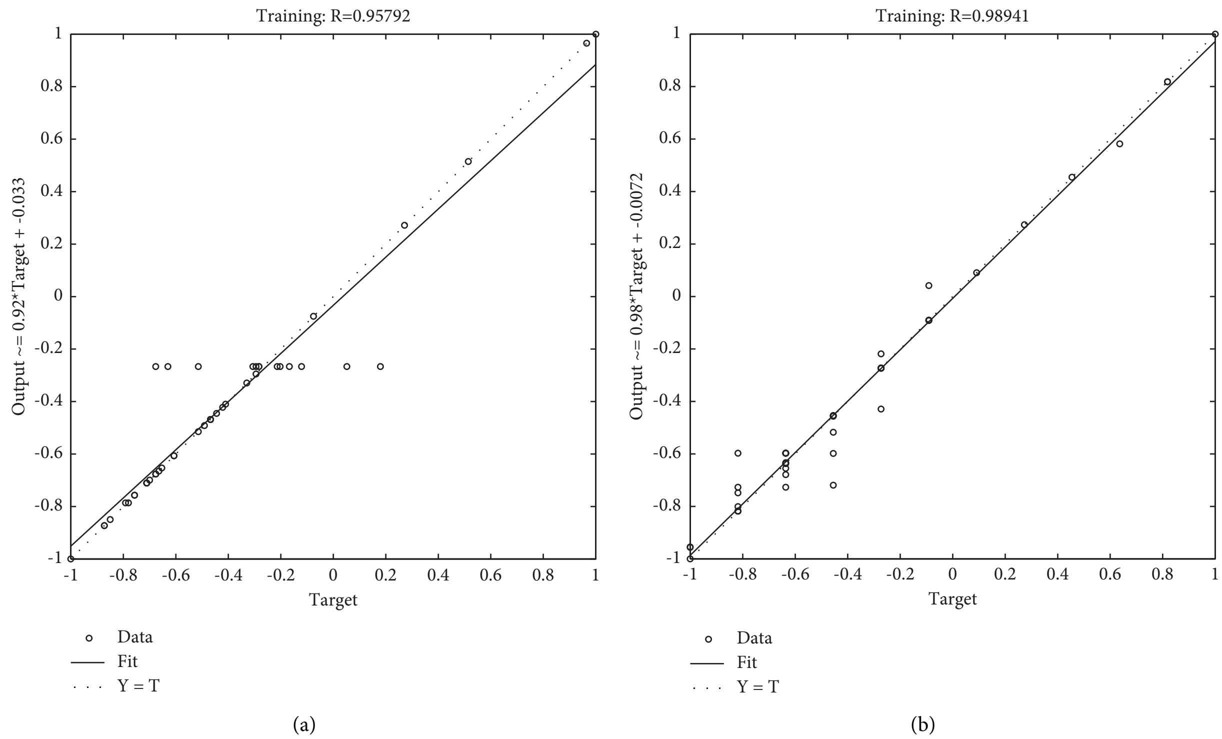

Figure 7: Accuracy of neural network training for scenario (1): (a) shows online shopping and (b) shows offline shopping.

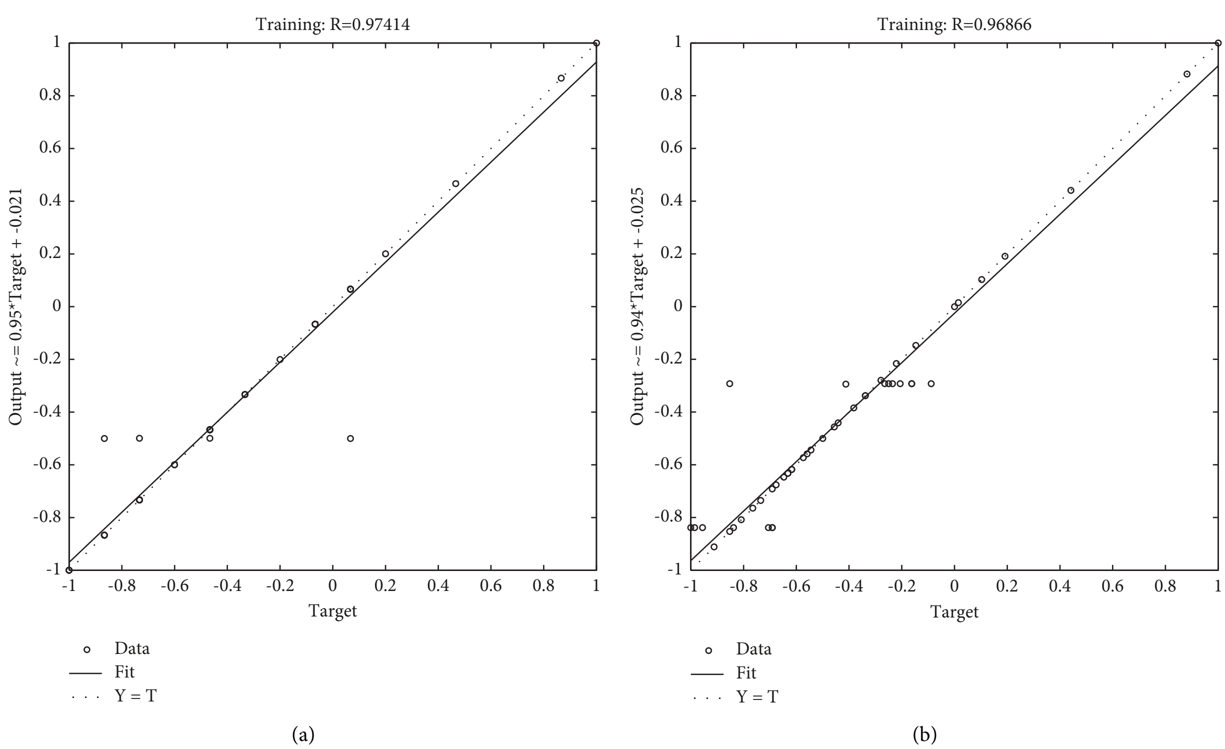

Figure 8: Accuracy of neural network training for scenario (2). (a) shows online shopping and (b) shows offline shopping.

Figure 12 shows how the goodness of fit of the QOL model varies with the number of iterations. When convergence is achieved, the goodness of fit values are 0.997, 0.997, 0.989, and 0.897. All of these values are greater than 0.6, suggesting that the fit is good.

Table 5 shows that in the scenario with new commodity transport services but without new passenger transport services ($i = 1$), δ_1, γ_{11}, γ_{12}, and γ_{13} are all greater than 0, and γ_{12} is the largest, followed by δ_1, which indicates that satisfaction with shopping in the Chunxiao CBD has the

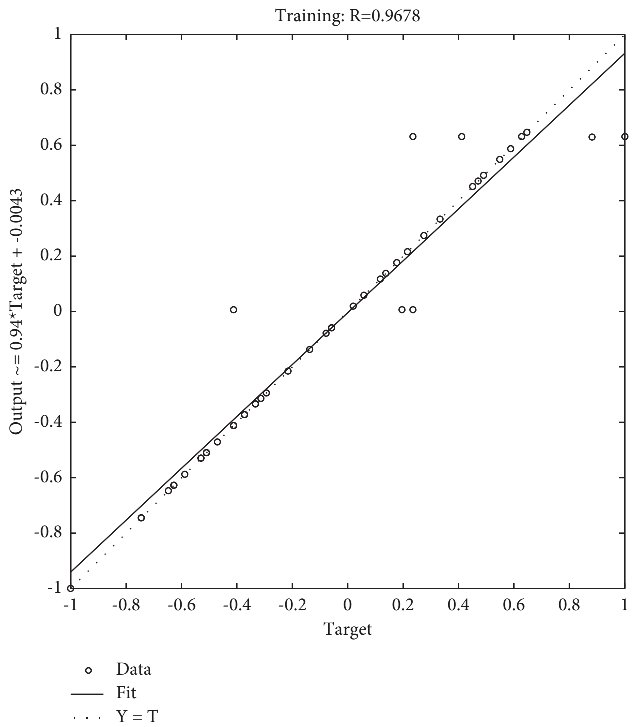

Figure 9: Accuracy of neural network training for scenario (3).

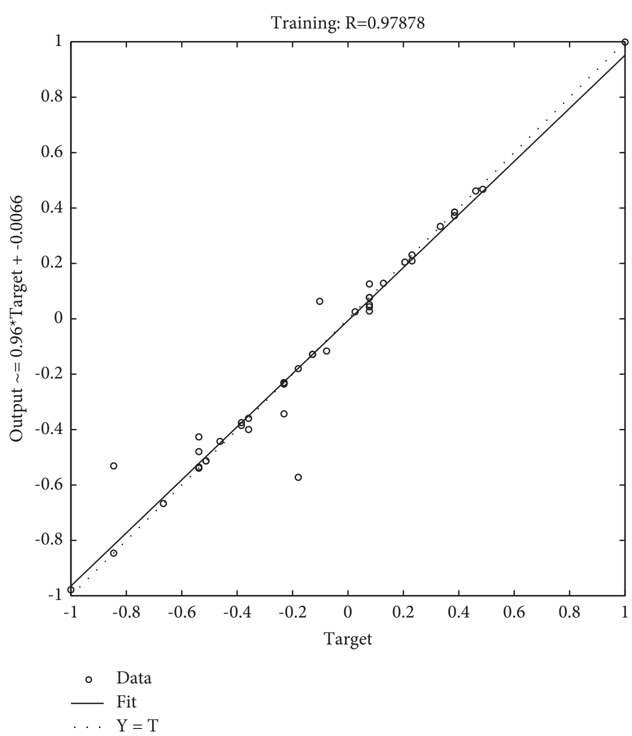

Figure 10: Accuracy of neural network training for scenario (4).

greatest impact on students' total shopping satisfaction, and the second-largest impact is observed for online shopping satisfaction. This is because in this scenario, e-commerce has been popularized, but TNC services are generally poor.

Table 4: Calibration results for equation (4).

Variable	Value	Standard error	Significance	t-value
Travel time	−0.900	0.180	0.000	−5.01
Travel cost	−0.027	0.013	0.041	−2.05
Comfort	0.026	0.038	0.000	6.74
Waiting time	−2.087	1.041	0.045	−2.00
Constant term	−0.774	0.326	0.018	−2.37

Online shopping is very convenient; thus, students are reluctant to go shopping at sites with high travel barriers (such as Yintai Plaza) and sites with poor atmosphere (such as nearby commercial streets). Therefore, online shopping became the main shopping channel. However, because students tend to value experiencing commodities before making purchases [56, 57], which online shopping cannot provide, once there are shopping sites (such as Chunxiao CBD) with low travel barriers and a relatively better atmosphere, students will prefer to choose such sites for shopping in B&MSs to experience commodities before making purchases.

In the scenario with both new commodity transport services and new passenger transport services ($i = 2$), δ_2, γ_{21}, γ_{22}, and γ_{23} are all larger than 0; among them, γ_{22} is the largest, followed by δ_2. This is because in this scenario, online shopping has matured, while TNC services and the shopping accessibility of B&MSs have improved. Students are more willing to go shopping in the Chunxiao CBD to enjoy their personal commodity experiences. Compared to scenario 1, the impact of satisfaction with shopping in the Chunxiao CBD on their total shopping satisfaction increased, while the impact of online shopping satisfaction decreased. This is because the improvement in travel accessibility in scenario 2 increases students' enjoyment of personally experiencing commodities and thus weakens the appeal of online shopping.

In the scenario without new commodity transport services but with new passenger transport services ($i = 3$), δ_3 equals to 0, which indicates that online shopping is unavailable. γ_{31}, γ_{32}, and γ_{33} are all greater than 0, and γ_{32} is the largest, followed by γ_{33}, which indicates that the impact of satisfaction with shopping in the Chunxiao CBD has the greatest impact on overall shopping satisfaction; additionally, the impact of satisfaction with shopping in Yintai Plaza is also important. This is because new commodity transport services are unavailable in this scenario; students cannot select online shopping, but with the help of new passenger transport services, the shopping accessibility of B&MSs has improved. Therefore, students are more inclined to go shopping in the Chunxiao CBD and Yintai Plaza. Students place high importance on shopping barriers when shopping at B&MSs. Compared with Yintai Plaza, the shopping barriers at for the Chunxiao CBD are smaller, which makes students more willing to shop in the Chunxiao CBD. Therefore, their satisfaction levels with shopping in the Chunxiao CBD have the greatest impact on their total shopping satisfaction.

In the scenario without new commodity transport or new passenger transport services ($i = 4$), δ_4 is 0, which

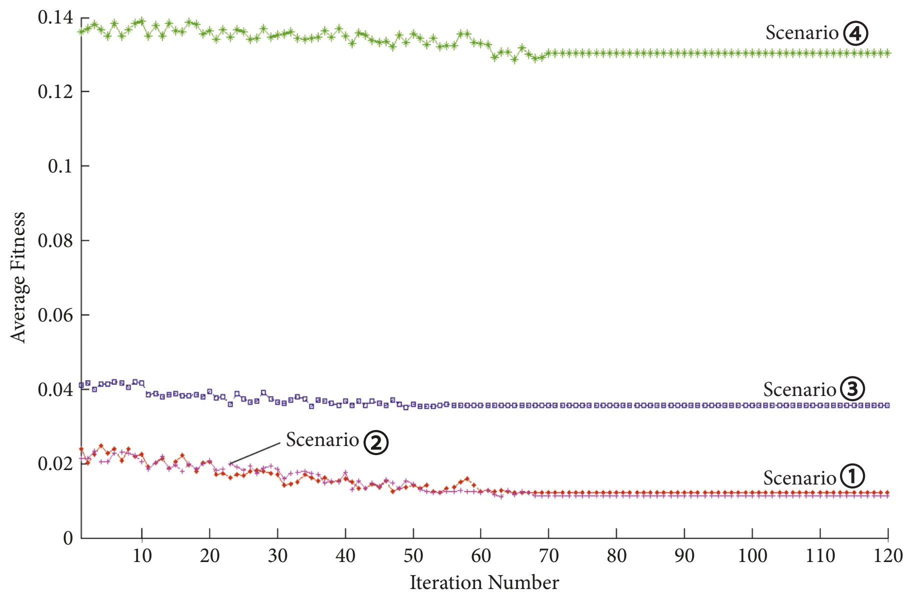

Figure 11: Convergence of the genetic algorithm.

Table 5: Calibration results for equation (17).

Variable	Parameter	Value			
		$i = 1$	$i = 2$	$i = 3$	$i = 4$
(i) Online shopping satisfaction	δ_i	0.31	0.29	0.00	0.00
(ii) Satisfaction with shopping on nearby commercial streets	γ_{i1}	0.19	0.15	0.26	0.29
(iii) Satisfaction with shopping in the Chunxiao CBD	γ_{i2}	0.32	0.35	0.42	0.39
(iv) Satisfaction with shopping in Yintai Plaza	γ_{i3}	0.28	0.12	0.30	0.21
(v) Gap due to store layout	α_{i1}	9.23	11.55	9.81	10.35
(vi) Gap due to in-store consultation	α_{i2}	2.36	1.95	10.59	8.54
(vii) Gap due to emotional attitude toward a store	α_{i3}	9.24	3.57	15.93	8.61
(viii) Gap due to disharmonious shopping atmosphere in a store	α_{i4}	6.82	18.15	13.79	1.54
(ix) Satisfaction with shopping accessibility	β_{i1}	1.35	2.78	7.49	3.93
(x) Satisfaction with service quality	β_{i2}	8.33	9.76	9.72	9.55
(xi) Satisfaction with commodity availability	β_{i3}	12.33	6.24	17.48	8.29
(xii) Satisfaction with commodity price	β_{i4}	6.72	5.84	13.53	5.90
(xiii) The number of purchases	τ_{ni}	5.65	9.19	6.92	8.73
(xiv) Shopping barriers	η_{ni}	11.68	18.70	19.91	18.73
(xv) Constant term for total shopping satisfaction	θ_i	140.74	199.08	−103.52	−36.57
(xvi) Constant term for shopping barriers	ϑ_i	4.85	18.85	17.90	13.68

Note. $i = 1$, 2, 3, and 4 denote the four scenarios.

indicates that online shopping is unavailable. γ_{41}, γ_{42}, and γ_{43} are all greater than 0, and γ_{42} is the largest, followed by γ_{41}, which indicates that satisfaction with shopping in the Chunxiao CBD has the greatest influence on total shopping satisfaction, followed by satisfaction with shopping on nearby commercial streets. This is because when TNC and online channels are not available, students could only go shopping in B&MSs but prefer nearby stores, especially stores in the Chunxiao CBD, due to the low travel barriers, good service, and abundant commodities.

In the four scenarios, the losses (α_{i1} and α_{i4}) caused by the store layout and disharmonious shopping atmosphere in stores, the satisfaction with service quality β_{i2} and the number of purchases τ_{ni} are the largest in the scenario with both a new commodity transport service and a new passenger transport service ($i = 2$). This finding suggests that the gaps caused by the store layout, a disharmonious shopping atmosphere in stores, service quality, and the number of purchases in scenario 2 have the greatest impact on the total shopping satisfaction in the four scenarios; the greater that the gaps created by store layout and disharmonious shopping atmosphere issues are, the greater that the shopping barriers are for the store, and the lower that the shopping satisfaction level is. The higher the students' satisfaction level with a store's services is, the greater the number of shopping instances and the higher the shopping satisfaction level.

In the four scenarios, the losses (α_{i2} and α_{i3}) caused by in-store consultation and consumer emotional attitudes, the satisfaction with shopping accessibility β_{i1}, the satisfaction

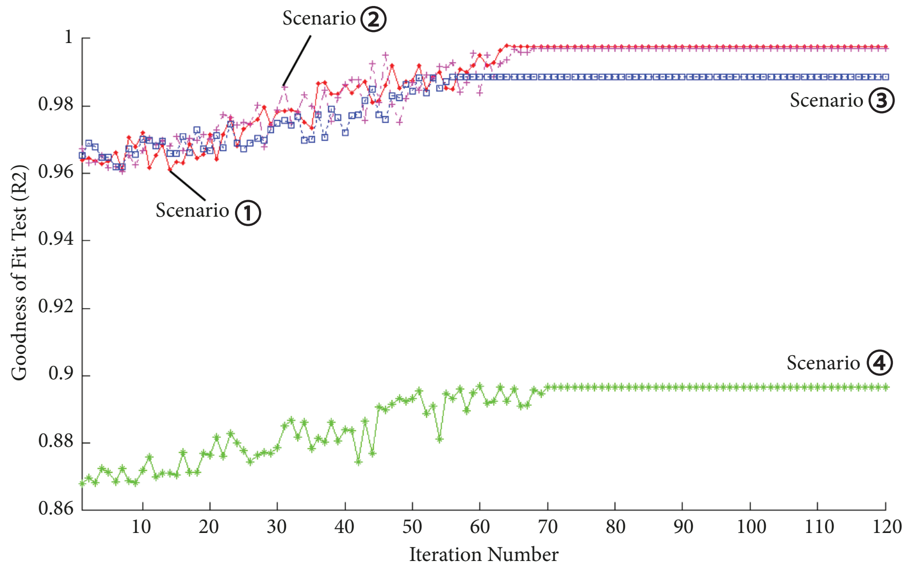

Figure 12: Convergence of the goodness of fit (R^2) for the QOL models.

with commodity availability β_{i3}, the satisfaction with commodity pricing β_{i4}, and the shopping barriers η_{ni} are the largest in the scenario without new commodity transport services but with new passenger transport services ($i = 3$). This finding indicates that the gaps caused by store consultation issues, consumer emotional attitudes, satisfaction with shopping accessibility, commodity availability, commodity pricing, and shopping barriers in scenario 3 have the greatest impacts on the total satisfaction of student shoppers; additionally, the greater that the gaps caused by store consultation issues and emotional attitudes toward stores are, the greater that the shopping barriers are, and the lower that the students' shopping satisfaction level is. However, the higher the students' satisfaction with shopping accessibility, commodity availability, and the price of commodities on sale is, the higher their shopping satisfaction levels.

5.4. Prediction of the Number of Instances with Purchases. Under the assumption that students' total shopping expenditures and QOL do not change, the following equation can be established:

$$\begin{cases} L_{ni} - L_n = 0 \\ \ln Q_{ni} - \ln Q_n = 0 \end{cases}, i = 1,\ 2,\ 3,\ 4, \tag{18}$$

where L_n is the living expense of student n, and Q_n is his or her QOL. To solve Eq. (18), a conversion is made to establish (19) as

$$\begin{cases} F_{1i}\left(X_{ni0}, X_{ni}\right) = L_{ni} - L_n \\ F_{2i}\left(X_{ni0}, X_{ni}\right) = \ln Q_{ni} - \ln Q_n \end{cases}, i = 1, 2, 3, 4. \tag{19}$$

Then, based on the idea of equivalent transformation, the problem of solving nonlinear equation systems can be transformed into the problem of minimizing the objective function [58–60]. Therefore, we further transform (19) to equivalently solve (20) as

$$F_i\left(X_{ni0}, X_{ni}\right) = F_{1i}\left(X_{ni0}, X_{ni}\right)^2 + F_{2i}\left(X_{ni0}, X_{ni}\right)^2. \tag{20}$$

The average value of each answer in the shopping activity survey (i.e., averages for the number of online purchases of daily necessities, school supplies, clothing accessories, food, electronic products, train tickets and prepaid/rechargeable cards, and cosmetics) over 4 months is calculated, and the results are used as inputs to solve the model and obtain the numbers of times students engage in online and offline shopping (Table 6).

After adding the new passenger transport service (Didi Travel) to the new commodity transport service (e-commerce), the monthly number of times of offline shopping and online shopping will be 5.455 and 3.454, respectively, which are significantly higher than the values of 4.398 and 2.792 in the case without new passenger transport services. This outcome indicates that a new passenger transport service can improve travel accessibility for B&MSs and save students' shopping trip costs, thereby increasing students' willingness to shop at B&MSs. Moreover, students can also use the saved money to do more online shopping or offline shopping to maintain their QOL. After adding new commodity transport services to new passenger transport services, the monthly number of online shopping sessions reaches 3.454, and the monthly number of offline shopping sessions is significantly lower than the 6.659 observed without new commodity transport services, which indicates that in addition to online shopping, students are still willing to shop at B&MSs. When new commodity transport services are unavailable, adding new passenger transport services can encourage students to shop offline because new passenger transport services will improve shopping accessibility and personal travel comfort and will save students' shopping trip costs, thereby leading to more shopping trips to B&MSs.

Table 6: Predicted number of shopping sessions (unit: sessions/person/month).

Scenario	Number of times: Online shopping	Number of times: Offline shopping
(1)	2.792	4.398
(2)	3.454	5.455
(3)	0.000	6.659
(4)	0.000	6.464

Table 7: Vehicles' specifications.

Transport process	Vehicle	Sources	Parameter value
LC-B&MS	Truck (name : Jianglin; ET: diesel; MTM: 8.28 t)	[61, 62]	$\rho_0 = 0.855$ kg/L $H_0 = 42.6$ MJ/kg $F_0 = 0.0741$ kg/MJ
LC-DC	Truck (name : Jianglin; ET: diesel; MTM: 4.50 t; ET: diesel)	[63, 64].	$\rho_0 = 0.855$ kg/L $H_0 = 42.6$ MJ/kg $F_0 = 0.0741$ kg/MJ
DC - TLDC	Truck (name : Naveco; ET: diesel; MTM:3.55 t; ET: diesel)	[65, 66]	$\rho_0 = 0.855$ kg/L $H_0 = 42.6$ MJ/kg $F_0 = 0.0741$ kg/MJ
Campus-B&MS	Car (name : Santana; ET: gasoline)	[67]	$O = 0.086$ L/km $\rho = 0.7 \sim 0.78$ kg/L $H = 46$ MJ/kg $F = 0.0693$ kg/MJ
	Public transit (name : BYD K8; ET: electric energy; seating capacity: 38)	[68]	$E_2 = 0.80$ (kW·h)/km $F_2 = 0.92$ kg/(kW·h)

Table 8: Carbon emissions related to shopping transport.

Scenario	Online shopping: DC-TLDC	Online shopping: LC-DC	Offline shopping: Campus-B&MS	Offline shopping: LC-B&MS	Total carbon emissions
(1)	71.58	10.66	9693.96	59.25	9835.45
(2)	88.55	13.19	58400.14	73.61	58575.49
(3)	0.00	0.00	76426.79	89.82	76516.61
(4)	0.00	0.00	14292.48	87.12	14379.60

5.5. Carbon Emissions Calculation. When calculating carbon emissions, it is assumed that trucks and Didi vehicles run on fossil fuels but that buses are electric vehicles. Some specifications of vehicles (including maximum total mass (MTM), energy type (ET), and parameters related to carbon emissions) are shown in Table 7.

By substituting the predicted number of shopping instances into Eq. (15), the monthly average total carbon emissions from the shopping-related transportation of the 3000 students on the whole campus can be calculated in the four scenarios, and the results are shown in Table 8.

When new commodity transport services are available, the emergence of new passenger transport services increases the total carbon emitted from shopping-related transport by a factor of nearly 6, and the total emissions reach 58575.49 kg/month. Among the four commodity transport modes (see Table 8), the carbon emissions from shopping transport from the campus to B&MSs increase the most, which indicates that new passenger transport services not only improve shopping accessibility but also increase shopping-related carbon emissions. When new passenger transport services are available, adding new commodity transport services can reduce the total carbon emissions because scattered personal shopping trips are replaced by cyclical trips made by delivery trucks; consequently, the students' shopping transport demands decrease, and the corresponding carbon emissions also decrease. In the scenario with new commodity transport services but without new passenger transport services, the total carbon emissions from students' shopping behaviors are the lowest, followed by those in the scenario without new commodity transport or passenger transport services. These results further suggest that new commodity transport services can reduce carbon emissions from shopping-related transport. The total carbon emissions in the scenario without new commodity transport services but with new passenger transport services are the highest, followed by those for in the scenario with new commodity transport and new passenger transport services. These results suggest that new passenger transport services may increase shopping traffic, thus increasing transport carbon emissions.

6. Conclusions

New transport services (e.g., Didi Travel or e-commerce) have changed consumers' shopping behaviors and shopping travel demands, thus affecting the carbon emissions of shopping-related transport. To study the impact of new transport services on consumers' shopping behaviors, university students who were relocated to outlying suburbs were studied, and four scenarios were established based on the availabilities of two new transport services; additionally, a shopping choice model (choices of shopping channels, of B&MSs, and of shopping trip modes) was established. Based on the shopping data obtained from a survey of university students who relocated to a campus in an outlying suburban area, we trained an artificial neural network (ANN) model for shopping channel choices and calibrated choices of B&MSs and of shopping trip modes. Using the models, the number of times students shopped online was forecasted in four scenarios, and the number of times students shopped in B&MSs and the corresponding shopping trip modes were estimated. An equation was developed to calculate students' total shopping expenditures (the amount of money used to purchase commodities plus the amount of money spent on shopping travel). Based on shopping satisfaction, a model for measuring students' QOL was established and calibrated with the data output from the shopping channel choice model. Finally, under the assumption that students' total shopping expenditure (revenue) and QOL remained unchanged, we estimated the number of student shopping trips in the four scenarios and compared and analyzed the impacts of new transport services on students' shopping behaviors. We also measured the carbon emitted from students' shopping-related transport and analyzed the effects of new transport services on carbon emissions.

The results show that due to new passenger transport services, consumers' number of shopping trips and the shopping-related transport emissions are increased by 24.03% and 495.55% (compared to (2) and (1)), respectively, in the cases in which new commodity transport services are available, while these two increments are 3.02% and 432.12% (compared to (3) and (4)), respectively, in the cases in which new commodity transport services are unavailable. This finding signals that new passenger transport services can improve students' shopping access to nearby commercial areas, increase students' shopping travel demands and lead to an increase in shopping-related transport emissions. Due to new commodity transport services, consumers' number of shopping trips and the corresponding shopping transport emissions are reduced by 31.96% and 31.60% (compared to (1) and (4)), respectively, and in the cases in which new passenger transport services are unavailable, while these two reductions are 18.08% and 23.45% (compared to (2) and (3)), respectively, in the cases in which new passenger transport services are available. This outcome indicates that new commodity transport services can reduce students' shopping trips, thus reducing the carbon emitted from shopping-related transport. When both new passenger transport services and new commodity transport services are available, the students are still willing to pay for travel services and shop offline to meet their hedonic shopping needs, despite that online shopping is more convenient. Additionally, the total carbon emitted from shopping-related transport in the scenario with new commodity transport services but without new passenger transport services is the lowest. This research may provide a reference basis for making policies to innovate retailing modes, provide new transport services, and optimize urban transport systems.

Three issues must be addressed when analyzing the impacts of new transport services on consumers' shopping behaviors and carbon emissions. First, when measuring consumers' total shopping expenditures, the categories and prices of retail commodities should be subdivided to ensure the accuracy of calculations. However, because sales prices differ across commodities, we could not obtain detailed statistics on the consumption of commodities purchased online or offline from the survey data. Therefore, we divided the commodities into only seven categories. Second, when performing statistical analyses of offline shopping data (namely, the category of offline purchased commodities, the number of trips to B&MSs, the modal splits of shopping trips, and the prices of the purchased commodities), real-time records should be tracked to ensure high prediction accuracy. However, technical support is needed to collect and store such records. Third, the impact of new transport services on total shopping expenditure (revenue) is dynamic, while this study only focused on the initial static stage, in which the new transport services have not changed consumers' shopping expenditures. We hope that we can address these issues in the future.

Data Availability

The data included in this study are available upon request by contact with the corresponding author.

Conflicts of Interest

The authors declare that there no conflicts of interest.

Supplementary Materials

The supplementary materials include the questionnaire sheet (Appendix A) for collecting the shopping data of students during the periods of September–December 2018 and September–December 2019. (*Supplementary Materials*)

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