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Research Article

The Interaction between E-Shopping and Shopping Trips: An Analysis with 2017 NHTS

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Advances in information and communication technologies (ICT) have dramatically changed the nature of shopping and the way people travel. As this technology becomes deeply rooted in people's lives, understanding the interplay between this way and personal travel is becoming increasingly important for planners. Using travel diary data from the 2017 National Household Travel Survey (NHTS) data for structural equation modeling (SEM) analysis, it revealed the interaction between e-shopping and shopping trips and the factors that affect this bidirectional relationship. Results show that e-shopping motivates shopping trips, and in-store shopping inhibits online shopping. It can be obtained that the increase of one standard deviation of e-shopping will increase the shopping trip by 0.17 standard deviation. When shopping trips increase by one standard deviation, e-shopping behavior also decreases by 0.12 standard deviation. The results also demonstrated that e-shopping and shopping travel behavior is heterogeneous across a variety of exogenous factors such as personal attributes, household characteristics, geography, travel distance/duration, and travel mode. Identifying the interaction may help formulate better transportation policies and lay the foundation for travel demand management strategies to reduce the stress on the transportation system and meet individual travel needs.

1. Introduction

The birth of the twenty-first century was dominated by one powerful trend affecting most aspects of life and economic progress, which is information and communications technology (ICT) [1]. Emerging technology is changing the way we perceive and tackle many modern issues, its influence in transportation planning is starting to be felt. Especially after the world experienced coronavirus disease (COVID-19), the changes brought about by ICT in our daily travel have received widespread attention. Mobile shopping apps are an application of ICT, which can facilitate online shopping (or e-shopping) [2]. Annual online retail sales in the US have grown from $27.608 billion (0.93% of total retail sales) in 2000 to $601.747 billion (11.01% of total retail sales) in 2019 [3]. It is expected that it will continue to influence people's shopping behavior and lifestyle, as it has a wide range of options and has ability to replace some certain flexible travel demand. For example, using mobile shopping apps, one can place orders online to replace flexible travel demand, such as eating out and shopping. Therefore, understanding personal shopping behavior can provide new insights into the application of ICT.

Under the background of a special period, ICT can realize the demand of staying at home, thereby reducing unnecessary travel demand and playing a role of self-protection. This is not only for the prevention and control of the epidemic but also brings adjustments to the transportation system and people's travel structure. ICT can affect daily travel through modification, substitution, and complementary effects. Transportation is not an end in itself. It is the ultimate goal to complete various tasks at the destination through travel, so travel is derivative. Productive travel demand such as commuting, business trips, and medical treatment cannot be completely changed by ICT. Among the elastic demand, only shopping travel demand can be replaced by ICT. Therefore, the relationship between online shopping and shopping travel has received widespread attention, and it is necessary to study the impact of ICT on shopping trips. Online shopping has an important impact on shopping, tourism, and transportation systems [4]. Travel demand for discretionary trips, such as shopping, has been one of the most common purposes for personal travel, accounting for 20% of trips in the US, European countries, and China [5, 6]. Early research found that e-shopping can generate more in-store shopping trips [7]. Consumers can easily obtain product information and prices, to confirm low-priced merchants before shopping trips, which will also burden the current lack of transportation [8, 9]. As shopping activities are highly influenced by individual decisions, the use of ICT may also act as an alternative to travel. Consequently, one of the most immediate and expected outcomes of e-shopping is a decline in physical shopping trips. With this promise, transportation scholars and research workers are interested in the relationship between online shopping and shopping trips in order to frame transportation policies and travel demand management strategies [10–12].

The overall daily trips per day reduced from 1995, as shown in Figure 1. Interestingly, the major decline due to the lower rate of trips for physical shopping coincides with the rise in online shopping and household deliveries [13]. According to the National Household Travel Survey (NHTS) 2017 survey results, more than half (i.e., 55%) of respondents indicated that they had made at least one online purchase in the last 30 days, and most of them had made an average of five online purchases [14]. Moreover, the number of home deliveries from online shopping has doubled between 2009 and 2017 [15]. Previous studies are based on hypotheses or conjectures to study the impact of e-shopping on shopping trips. Then, e-shopping and shopping trips will influence each other, and this paper is based on this interesting discovery to explore the bidirectional relationship. To fill the gaps in existing research, this research examines the conceptual basis of existing theories to identify the characteristics of shopping trips that lead people to traditional and technology-based activities. In other words, this research aims to investigate individuals' online and in-store shopping travel behavior. Most studies use empirical data from a specific field or assume some prerequisites for a small sample. In this context, it is imperative to analyze the interaction between e-shopping and shopping trips based on comprehensive datasets. In order to explore the shortcomings in the past research, we used rich datasets and comprehensive quantitative models to study the interaction between e-shopping and shopping travel and, at the same time, determine which variables affect traditional shopping trips and e-shopping. The remainder of this paper is organized as follows. Section 2presents a theoretical framework. The description of the research method is carried out in Section 3. Section 4continuously explains about results. Finally, the conclusions of the research findings are summarized in Section 5.

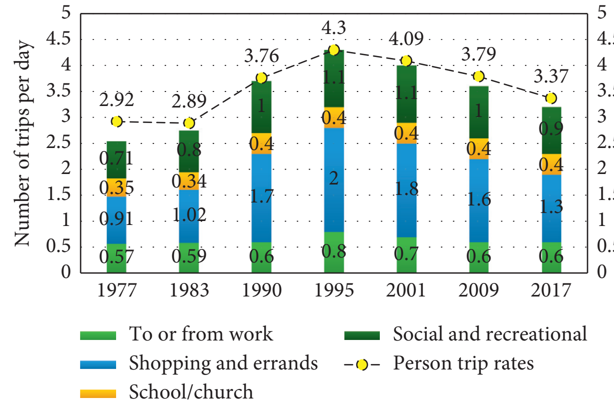

Figure 1: Number of daily trips per person by purpose: 1977, 1983, 1990, 1995 NPTS, 2001, 2009, and 2017 NHTS.

2. Theoretical Framework

2.1. E-Shopping and Personal In-Store Shopping Trips. In the light of the explosive growth of the Internet, the widespread of online shopping has brought implications on personal travel and physical shopping trips, which attracted the interest of academicians and researchers since the mid-to-late 1980s [16]. At that time, transportation planning academicians and especially practitioners studied the potential impacts of telecommunication on transportation, and most of the relevant research studies have drawn the conclusion of the substitution relationship. Subsequently, the other types of impacts on transportation have not escaped the notice. Salomon and European Conference of Ministers of Transport [17, 18] identified a more complex picture of the relationship: substitution, complementarity, and neutrality. Some scholars argue that this interaction goes beyond relationship between the use of technology and the number of physical trip, considering a wider range of qualitative interactions that associated with individual spatiotemporal and relational behavior [19]. As mentioned above, this typology has been updated and widely applied in empirical research to understand the interaction between virtual mobility and shopping trip in subsequent works [12, 20–23]. Conceptually, transportation scholars proposed four conceptual effects of ICT on travel behavior: substitution, complementarity, modification, and neutrality [16, 17]. A substitution effect refers to e-shopping acting as a substitute for shopping trips because there is no need for people to make a physical mobility to accomplish the goals of goods acquisitions. A complementarity effect denotes the extent to which e-shopping may stimulate the desire of shopping and increase more shopping trips, as it can offer more shopping information, resulting in generating more physical trips based on travel time budget theory [24, 25]. Modification means that online shopping can change the characteristics of trips such as route, mode, and time. There are also studies suggesting that e-shopping does not influence in-store shopping, which is neutrality.

Many scholars tend to focus only on unilateral effects and conduct empirical studies on these conceptual connections. Most of the research focuses on the influence of e-shopping on people's travel behavior. Some studies have confirmed the substitution effect of e-shopping on shopping trips in the US [26] and Indonesia [27]. Research in the Netherlands found that a high frequency of searching online is more likely to make shopping trips [28]. Evidence from the United States confirms this finding. For example, Cao et al. [29] found that 49.3% of respondents made more trips after searching online, which provides evidence for the complementarity effect on physical store shopping. In a Scottish Isles study, Sim and Koi [11] revealed that e-commerce not only has no significant impact on consumers' travel patterns but also the travel patterns will be weakened by other situational factors. Salomon [30] concluded that the substitution of information and communication technologies for travel is of minor importance because the net effect is a modification of travel rather than a reduction of volumes.

It is not only e-shopping that has an impact on shopping trips but shopping trips also influence e-shopping behavior. The early research was carried out by Farag et al. [31] using the shopping survey data of 826 interviewees; the author studied the relationship between web search frequency, online purchase, and nondaily shopping trips by SEM. After accounting for the mixed effects of demographics, shopping attitudes, and lifestyle, they concluded that e-shopping had a positive effect on shopping trips, which also spurred more e-shopping. The study using NHTS datasets came from Zhou and Wang [32]. The author established the SEM model, applied the data in 2009 to explore the correlation, and found that online shopping has a complementary effect on shopping trips, but shopping trips often replace online shopping. Research from China has found that online shopping has a significant impact on bricks-and-mortar shopping and other individual activities such as leisure activities and travel chain behavior [33]. Using GPS-based activity travel diary data from Beijing, this paper investigates the relationship between online shopping, in-store shopping, and other dimensions of activity travel behavior using a structural equation modeling framework. Therefore, the interaction between e-shopping and physical store shopping is uncertain.

The literature offers mixed empirical results that cannot reach a consensus on the relationship and sometimes provide a dual conclusion [34]. The conclusion is far from reaching the consensus due to the different empirical contexts, geographical scales, different assumptions, variables, data sources, and methodologies involved. Although the results are inconsistent, a significant relationship between online shopping and travel behavior might be demonstrated by numerous studies, although the extent varies. However, the relationship between virtual and physical mobility is suggested to vary depending on the variation of socioeconomic groups, area distinctions, and location characteristics. Most existing research studies are based on some certain assumption; then, they try to collect data to analyze what they want. A few studies are discussing this topic based on real comprehensive travel diary data.

Results are easily influenced by what methods are used in the analysis, which variable to be measured, how to classify these variables into one measure dimension (e.g., personal-related, travel-related, web use experience-related, and demographic), research design, sample size, and other assumptions. Another common challenge is collecting appropriate datasets as some travel surveys are subject to sample size and regional variation. On the method level, at the early stage of research studies on exploring the interplay between e-shopping and shopping trips, correlation and linear regression analyses were widely applied (e.g., [28, 29, 33]). As one crucial deficiency of correlation and regression modeling is that it is not capable of modeling the reciprocal influence among dependent variables. Accordingly, some of these results neither revealed the in-depth effects of online shopping on shopping trips nor did the results consider the characteristics of different factors. In the analysis of multiple independent variables and dependent variables, structural equation modeling (SEM,e.g., [19, 27, 32, 35]) is undoubtedly the better choice. The innovative feature of SEM allows researchers to test a set of regression equations simultaneously [36]. In this context, a comprehensive sample data from NHTS 2017 can conduct an overall analysis through SEM which will provide further insights into this issue.

2.2. Structural Equation Modeling. Most of the previous studies were limited to simple linear correlation analysis, such as binary logit model, multinomial logit model, path analysis, and probit model, but ignored the complex relationship between variables, as shown in Table 1. With the deepening of research, the influencing factor variables of the relationship gradually increase, requiring statistical research techniques to deal with the potential relationship between these variables. Traditional statistical analysis techniques (the univariate *t*-test, ANOVA, multiple regression, descriptive discriminant analysis, and correlation analysis) can only measure the direct influence relationship between independent variables and dependent variables, but the complexity of this interrelationship determines the interdependence between independent variables, which has an indirect impact on it. Clarifying the relationship between different influencing factors and clarifying the direct and indirect influencing factors of online shopping and physical shopping are the premise and foundation of building the relationship model. The interaction mechanism between the above influencing factors and their interaction with travel modes can be revealed by the structural equation model (e.g., [11, 16, 19]).

In recent years, structural equation modeling (SEM) becomes an approach that is extensively employed in travel behavior analysis. SEM is capable of exploring and analyzing the direction and strength of various relations in many research fields since it is a powerful analytical tool to process multiple dependent variables simultaneously [38]. For example, Farag et al. [7] studied the effect of searching online frequency on e-shopping and physical shopping and the complex relationship between this online activity and in-store shopping trips by using SEM. SEM is a statistical modeling technique that combines factor analysis with

Table 1: Summary of methods and conclusions.

Study	Methodology	Key variables	Conclusion
[28]	SEM	Socio-demographics, shopping enjoyment, income, shopping accessibility, shopping responsibility, shopping behavior, shopping attitude, and Internet experience	A complementary effect of online shopping on in-store shopping
[11]	SEM	Internet-related, regional-specific, household-related, personal-related, and travel pattern-related	Online shopping encourages shopping trips; shopping trips discourage the online shopping
[29]	Regression models	Sociodemographic, travel time, Internet experience, and attitudinal	E-shopping has a substitution effect on the frequency of shopping trips
[33]	SEM	Sociodemographic factors, Internet experiences, spatial attributes, car ownership, and type of work	Online shopping can replace the shopping travel demand
[37]	Multinomial logistic model	Socio-demographic, Internet use, travel time, and trip frequencies	Online shopping was positively associated with travel for shopping
[20]	Path analysis	Socio-demographics factors, land use, behavioral, and attitudinal variables	Complementarity
[6]	Binary logit	Sociodemographic factors, Internet-use variables, and geographic-context variables	People with lower levels of accessibility to local shopping, and white people are more likely to adopt online shopping

regression or path analysis to analyze the structural relationships. There are two main components of the model: a measurement model and a structural model. A measurement model is the relationship between latent variables (an abstract concept cannot be measured directly) and observed variables (can be measured directly). The structural model is used to define the potential causal dependencies between latent independent variables and latent dependent variables. Therefore, a structural equation model is as follows [38]:

$$\eta = \gamma\xi + \beta\eta + \zeta, \tag{1}$$

where $\eta = p \times 1$ is the vector of latent endogenous variables, $\xi = q \times 1$ is the vector of latent exogenous variables, $\zeta = y \times 1$ is the vector of equation errors, γ, $\beta = p \times q$ is the matrix of the coefficient of the latent exogenous, and $p \times q$ is the matrix of the coefficient of the latent endogenous.

In the measurement model, since the assumed construct cannot be directly measured, the observed, recorded, or measured is constructed as latent variables by the measurement model. It refers to the relationship between the latent variable and observed variable. The basic equation is as follows:

A measurement model of endogenous: $Y = \lambda\eta + \varepsilon$

A measurement model of exogenous: $X = \lambda\xi + \delta$

SEM also identifies the direct, indirect, and total effect [8]. Direct effect reflects the direct influence of the cause variable (exogenous or endogenous variable) on the result variable (endogenous variable), and its magnitude is equal to the coefficient of the path from the cause variable to the result variable, while the indirect effect represents the sum effects of two variables through intervening variables. Finally, the total effect is the sum of the effects of cause variables on effect variables, including direct and indirect effects.

2.3. Parameter Estimation Strategy. In structural equation models, there are at least several methods to evaluate each parameter: instrumental variable method (IV), two-stage least squares (TSLS), unweighted least squares (ULS), generalized least square (GLS), maximum likelihood (ML), elliptical distribution theory (EDT), and asymptotically distribution-free (ADF) estimator [39]. The common point of these different methods is to obtain the minimum value of the difference between observation and estimation of covariant structures to derive the best estimate of a parameter. When the normality hypothesis is violated, ML and GLS are used to estimate the parameters, and the sample size must reach more than 2500 before the parameter estimation becomes stable [40]. Scaled ML performs best with medium to large sample sizes. ML has been the predominant estimation method as a whole system estimation method suitable for large sample size [41]. Thus, this paper adopted ML as an estimated approach.

2.4. Statistical Analysis. SPSS 23.0 was applied to calculate the descriptive statistics, and AMOS 24.0 was used to conduct structural equation modeling (SEM) to identify the interaction between e-shopping and shopping trips.

3. Data and Method

3.1. Data Collection. This paper uses travel diary data from the 2017 NHTS (National Household Travel Survey) dataset. NHTS is conducted by the Federal Highway Administration (FHWA) and collecting data related to the travel behavior of the American public which can be used to analyze the trends or characteristics of personal and household travel [42]. It is the only authoritative source of national level on personal travel in the United States. The 2017 NHTS data was to get completed surveys from a stratified random sample of 129,696 households, including 264,234 individuals aged 5 and older in the US, 256,115 vehicle samples, and 923,572 trip samples.

Despite the NHTS covering many household travel information, it was the first time that NHTS referred to online shopping data in 2009. Then, the data series added questions about online shopping for the second time in the

2017 NHTS. The full NHTS 2017 dataset involves a very large sample and a piece of comprehensive information that can sketch a profile of travelers. The value of the data has been demonstrated in many other topics of the transportation research field, such as active transportation among minority youth [43], the trend of ride-hailing [44], travel patterns of older adults [45], and alternative travel mode [46]. In short, the 2017 NHTS is the most recent, reliable, authoritative, and comprehensive dataset for the study on travel behavior.

Until now, no study has used this latest 2017 dataset to analyze the interplay between e-shopping and travel demand for shopping. This article is the first attempt to apply these data to explore the analysis. The results will enrich existing research in this realm and help practitioners devise strategies to manage in-store shopping demand.

The 2017 NHTS data are primarily related to daily travel, including individual personal, household characteristics, socioeconomic characteristics, vehicle ownership, and vehicle attributes. Therefore, there are four files including household file, person file, vehicle file, and travel Day trip file. Despite the effort to include many variables in each file, sometimes one research topic may need to use information from separate files. In this type of circumstances, it would be necessary to merge two or more of the four files to gain an integrated dataset that includes the travel information this study needs before performing analysis. The unit of analysis in this study was the person. The number that identifies a trip taken by an individual needs to be used in conjunction with the person's unique ID (i.e., HH Person ID and PERSONID) to uniquely identify those trips [47]. After the merging, each record in the resulting table should correspond with a unique personal-specific variable, such as the personal file, including 21 variables and 173,500 sample size. This is because the personal file contains the specific file of personal information. The framework for the integrated database that involves traveler's characteristics and trip information obtained by aggregating the household file and trip file, as shown in Figure 2.

3.2. Model Specification

3.2.1. Measurement Model Hypothesis. The measurement model refers to describe whether the observed variables are suitable as the measurement means of latent variables. By establishing the interaction between the observed variables and the measured latent variables, a data test is used to verify the existence of a hypothetical structure. Based on many previous studies, this paper assumes that the measurement model is composed of five exogenous latent variables: personal attributes, household characteristics, geography, travel-related, and travel pattern-related. Each exogenous latent variable is reflected by several measurable exogenous factor observation variables, as shown in Table 2.

Similarly, it is assumed in this paper that the measurement model is composed of two endogenous factor latent variables, including the propensity of online shopping and propensity of shopping trips. Each endogenous factor latent variable is also reflected by several measurable endogenous factor observation variables, as shown in Table 3.

3.2.2. Structure Model Hypothesis. This paper assumes that there is an interaction between the two external factors of the structural model and that the personal attributes, household characteristics, geography, travel-related, and travel pattern-related to having an impact on all the internal latent variables. Figure 3 illustrates the structural relationship between e-shopping and shopping trips, and other dimensions of activity travel behaviors. Web use means the number of Internet use. Deliver means the number of online purchasing.

3.2.3. Research Model Assumptions. This paper proposes five hypotheses for the research model: (1) each test item has a load that is not 0 on the potential variable it is measured, but a load of other latent variables is 0; (2) there is no correlation between the test items and the related measurement error items; (3) there is no correlation between latent variables and residual terms between latent variables; (4) there is no correlation between the residual term of the latent variables and the measurement error term; (5) interference is unrelated to exogenous latent variables.

3.3. Variable Selection

3.3.1. Exogenous Variable. Exogenous variable refers to the variable that is not affected by any other variable in the model, but directly affects other variables. In terms of personal attributes, there are five exogenous observed variables: gender, age, education background, job type, and driver status. Many studies have found that education level, gender difference, and income gap may have different effects on e-shopping behavior. In terms of household characteristics, there are four exogenous observed variables: income level, household size, vehicle ownership, and family with no children. Family characteristics also affect shopping trips and e-shopping. Families with more income may have more shopping behaviors, and families with more cars are more inclined to travel. In terms of geography, it is urban or not and population density. In terms of travel-related information, it is total travel miles and total travel duration. Different geographical locations also have different effects on online shopping and shopping trips. For example, due to the serious traffic congestion in big cities, travel is restricted, and office workers are more willing to go shopping at home. In terms of travel mode, it is private vehicle, active transportation, and public transportation. Different modes of trips also affect people's shopping trips. The descriptions of variables and key statistics are listed in Table 4.

4. Discussion

4.1. Descriptive Statistics of the Sample. The means and standard deviations of the continuous variables, the frequency, and the percentage of the classified variables are given in Table 4. Note that, in this study, we focus on the

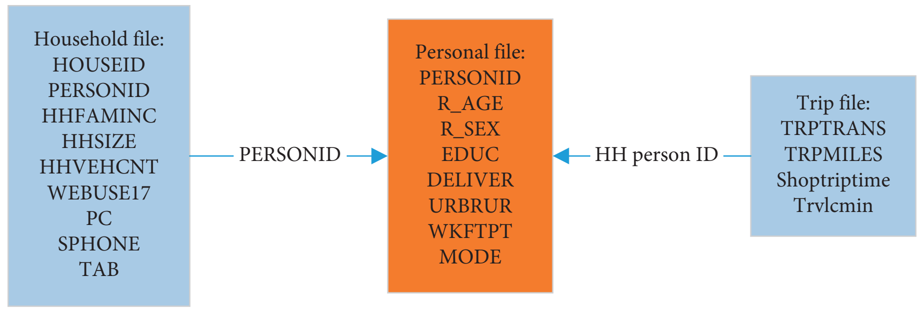

Figure 2: A framework for data consolidation.

Table 2: The hypothesis of exogenous latent variables.

Exogenous latent variable	Observed variable
Personal attributes	Gender, age, education attainment, type of work, and driver status
Household characteristics	Household income, household member, vehicle ownership, and household type with one or more adults no children
Geography	Urban or not and population density
Travel-related	Total travel miles and total travel duration
Travel mode	Private vehicle, active transportation, and public transportation

Table 3: The hypothesis of endogenous latent variables.

Exogenous latent variable	Observed variable
E-shopping propensity	Web use and deliver
Shopping trips propensity	Shopping trip time, shopping trip mile, and shopping trip duration

interaction between e-shopping and shopping trip behavior; therefore, all the variables are related to e-shopping and shopping trips. The observation with missing data and respondents younger than 16 years old was omitted from the sample, and a total of 173,500 records were obtained by controlling the sample quality. More specifically, the average age in the sample was 56.8; the female accounted for 56.4% of all the respondents. Nearly half of the respondents had a bachelor's degree or higher, accounting for 45.7%. One in three performed a full-time job. Among these respondents, 94.6% were drivers. For the sample, 43.1% of household income was more than \$75,000. The average household member is 2.3. The average car ownership is 2.1. One or more adults with no children accounted for 0.8%. The proportion of the respondents whose household location in the urban is 76.5%. The average total travel distance was 41.8 miles, and the average total travel duration was 77.6 minutes. Of those people who ever purchased online in the last 30 days is about 2.7 times on average. Average shopping trips were about 3. 3 times, and the average shopping trip mile was 15.5 miles. The average duration of shopping trips was 36.6. Table 4 displays the descriptions of variables pertaining to the analyzed sample.

4.2. Model Text. The goodness-of-fit of DEM is to judge to what extent the specified model fits the empirical data [48]. After the model was successfully constructed, it is necessary to measure the goodness of fit for both the measurement model and structure model. Hair et al. [49] said that applying 4-5 goodness-of-fit is satisfactory enough to assess the feasibility of the model. The drawback of χ^2 text is that the chi-square value is very sensitive to the size of the sample. Due to the sample size in this study is very huge, we cannot use CMIN/DF to judge the goodness-of-fit in this study. Therefore, we choose the goodness-of-fit (GFI), AGFI, comparative fit index (CFI), Bentler-Bonett normed fit index (NFI), IFI, TFI, and the root mean square error of approximation (RMESA) for evaluation text. According to the result of the modification, indices are used to modify the final model by applying the maximum principle. The result of goodness-of-fit for the model is displayed in Table 5.

4.3. Model Result and Analysis

4.3.1. Relationships among Endogenous Variables. The main function of the SEM is to reveal the structural relations between latent variables (between latent variables and measurable variables and between measurable variables), which are reflected in the model through the path coefficients (load coefficients). The path coefficients are not normalized and are called nonnormalized coefficients. In the nonstandardized coefficient, there are measurement units dependent on relevant variables, which cannot be directly used in the comparison of path coefficient (or in the comparison of coefficient). The standardized coefficient can be used to directly compare the effects of different

Table 4: Descriptions of variables and key statistics.

Variables	Mean	Std. dev	Frequency	Percentage
Exogenous variable				
Personal attributes				
(1) Age (continuous)	56.8	16.5		
(2) Gender (1 for female; 0 otherwise)			97891	56.4
(3) Education level (1 for bachelor or more than; 0 otherwise)			97368	45.7
(4) Work type (1 for full time; 0 for part time)			56272	32.4
(5) Driver status (1 for yes; 0 for otherwise)			164060	94.6
Household-related				
(1) Income (1 for income >$75000; 0 otherwise)			71711	41.3
(2) Household member (continuous)	2.3	1.2		
(3) Household vehicle (continuous)	2.1	1.2		
(4) One or more adults and no children (continuous)			1464	0.8
Geography				
(1) Urban (1 for yes; 0 otherwise)			132795	76.5
(2) Population density (continuous)	3788.2	5232		
Travel-related		.		
(1) Total travel distance (continuous)	45.9	129.8		
(2) Total travel duration	102.2	84.4		
Mode to work				
(1) Private vehicle (1 for yes; 0 otherwise)			161592	93.1
(2) Active transportation (1 for yes; 0 otherwise)			1856	1.1
(3) Public transportation (1 for yes; 0 otherwise)			1464	0.8
Endogenous variable				
Deliver (continuous)	2.7	4.3		
Web use (continuous)	1.3	0.9		
Shopping trip (continuous)	3.3	2.6		
Shopping trip mile (continuous)	15.5	49.9		
Shopping trip duration (continuous)	36.6	43.6		

coefficients. Therefore, the estimated results are analyzed according to the standardized coefficient.

This section mainly discusses the interaction between e-shopping and physical shopping trips. As we can see from Figure 3, the model is nonrecursive and has some kind of feedback loop between two variables that have reciprocal causation. The path coefficient from the cause variable to the result variable measures the direct effect. Based on the output of the path diagram in Figure 4, there are two main discoveries in this subject. The result is consistent with the findings from Zhou and Wang in 2014. The first is that the standardized coefficient of e-shopping propensity on shopping trips propensity is 0.22, which has a significant positive impact on shopping trips. It means that making more online shopping has a positive influence on physical store shopping. This result explicitly reveals that online shopping can encourage the willingness to purchase products in store. As shown in Table 6, it can be concluded that if the e-shopping propensity increases by one standard deviation, the shopping trips propensity will eventually increase by 0.17 standard deviation. It seems that the marginal impact of store shopping on online shopping is 0.17. The second outcome is the standardized path coefficient of "shopping trips" on "e-shopping" is −0.09. Such a negative effect means that the intensity to do in-store shopping tends to do e-shopping less. Although the value of the effect is not large, the relationship is negative, as indicated by the total effect of −0.12. The marginal impact of in-store shopping on e-shopping is −0.12. Frequent shopping trips would decrease e-shopping at the same time, probably because the in-store shopping experience offers a better shopping experience. Hence, people who make more shopping trips are less likely to shop online.

4.3.2. Determinants of E-Shopping Frequency and Shopping Trip Frequency. Important findings of the relationship between exogenous variables and shopping propensity, quantifying these effects through direct effects, are shown in Table 7. First is the factor of personal attributes. It consists of gender, age, education attainment, type of work, and driver status. As expected, females tend to undertake shopping trips and less likely to shopping online, which is consistent with the literature [33, 50]. Ding and Lu [33] explained that women are more inclined to the online shopping activity, compared to men. As people get older, they are more likely to go outside to do shopping and less likely to shop online. This is to be expected, as young people are generally more receptive to new technology or new alternatives and are more likely to shop online. Older people have more desire to travel outside. They might be more conservative and not be familiar with the new modes of payment. Other empirical studies also found that the aged prefer online shopping to in-store shopping [27, 31–33, 50]. People with a bachelor's degree or above are more likely to adopt new technologies to replace traditional mobile travel due to their better educational ability and adaptability, which is in line with many previous studies [51–54]. Additionally, respondents with a higher educational background are making more shopping

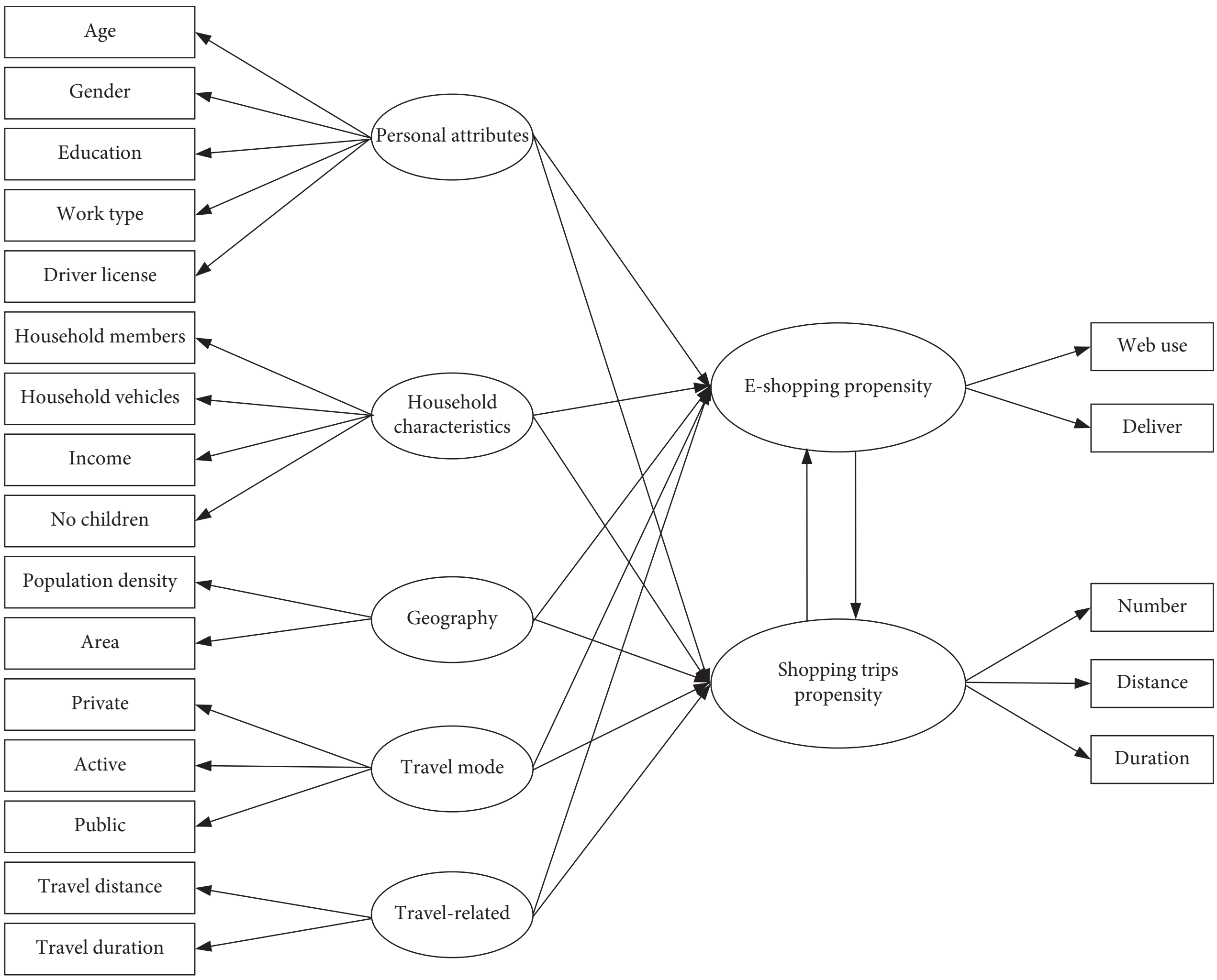

Figure 3: Structure of the model.

Table 5: Goodness-of-fit test.

Fit indices	Recommended value	Tested model
GFI	≥0.9	0.944
AGFI	≥0.9	0.921
CFI	≥0.9	0.926
NFI	≥0.9	0.925
IFI	≥0.9	0.926
TLI	≥0.9	0.871
RMESA	≤0.0.8	0.059

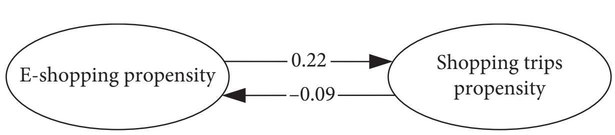

Figure 4: The output of the path coefficient.

trips, which supports the finding of [11]. As for the work type, a full-time worker is inclined to purchase online frequently and make fewer shopping trips, which is the same as the finding of [28]. Possession of a driver's license prevents people from being restricted by distance, thus allowing them to engage in more travel and shopping activities, which seems to contradict the findings of [27].

With regard to household characteristics, which contains household income, household member, vehicle ownership, and family type, income is positively associated with shopping trips, possibly because affluent people tend to be less price-sensitive and more real-life shopping oriented [11, 55]. This result is consistent with the findings by [14]. Households with more vehicles and family members are positively associated with shopping trips. A household without children shops is online more frequently but less likely to do real-life shopping experiences. In terms of geography, we mainly focus on the household area and population density. The urban area also contributes to the explanation of high frequency of shopping activities. The respondents living in the urbanized area and higher population density are also prone to making more shopping activities online not in-store. Bad traffic conditions might restrict people's mobility. This finding might suggest that location plays a vital role in shopping and travel behavior, which meant the higher accessibility to the physical store and ICT capability might result in higher interest in shopping trips. For example, heavy congestion and tight schedules may

Table 6: Total effects of endogenous variables.

	E-shopping propensity	Shopping trip propensity
E-shopping propensity		−0.12***
Shopping trip propensity	0.17***	0

*denotes $p < 0.05$; **denotes $p < 0.05$; ***denotes $p < 0.05$.

Table 7: Coefficient of standardized total effects.

	Endogenous variables	
	E-shopping propensity	Shopping trip propensity
Personal attributes		
Age	0.078***	−0.508***
Female	−0.006***	0.039***
Bachelor and above	0.017***	−0.112***
Full-time job	0.054	−0.353
Drive state	−0.006	0.04***
Household-related		
Income	−0.172	0.027
Household member	−0.01***	0.344***
Household vehicle	−0.005***	0.064***
Family with no children	0.003***	−0.087***
Geography		
Population density	0.146	−0.283***
Urban	0.036	−0.07
Travel-related		
Total travel distance	−0.12	0.067***
Total travel duration	−0.005	0.031***
Trip mode		
Private transportation	0.18	0.272**
Active transportation	−0.032	−0.048***
Public transportation	−0.085	−0.128***
Web use	0.509***	
Deliver	0.353***	
Shopping trip		0.334
Shopping trip mile		0.571***
Shopping trip duration		1.012***

*denotes $p < 0.05$; **denotes $p < 0.05$; ***denotes $p < 0.05$.

reduce the frequency of shopping trips for urban residents. Total travel distance and total travel duration are all positively related to shopping travel demand. People who spend more time on daily travel have a greater possibility of shopping trips, and the longer travel distance also stimulates the demand for shopping trips. This can be interpreted that transportation conditions may impact online shopping and shopping trips. Moreover, travel demand as a latent demand might be influenced by various travel purposes. With respect to the trip mode, the following results were obtained. Individuals who use public transportation and active transportation experienced fewer shopping trips yet had high online shopping orientation, while the reversed result was identified from those who take a private vehicle. Those individuals who rode a private vehicle are more likely to undertake more shopping trips and online shopping because they are not limited by weather and distance as well. As we knew, the automobile promoted the spatial dispersion of stores and increased the travel distance of shopping. This has a rather interesting explanation: public and active transportation users are more likely to be pressured by time to get to their work destination as a result of requiring more time to travel to their destination. However, it still needs further study for why active and public transportation users make fewer shopping trips. This finding sheds light on the travel mode that might have an impact on the purpose of trips. Web use and deliver frequency are well-measured variables for endogenous variables.

5. Conclusions

With the development of ICT, the impact of online shopping on travel behavior is changing and it is difficult to predict. According to previous literature, the definition of this interaction is controversial, and it remains unclear whether it is pure substitution or pure complement. Exploring the interaction between e-shopping and shopping trips is the key to study the impact of ICT on flexible travel demand. In this paper, the NHTS 2017 database was used for the first time and structural equation modeling (SEM) was established to reveal the factors affecting shopping trips and online shopping and their interaction. Overall, the survey results show a subtle and complex relationship between e-shopping and personal shopping trips. The results show that e-shopping has a complementary effect on physical shopping, that is, e-shopping activities will lead to the increase of shopping travel demand, but real shopping activities will inhibit e-shopping. This result is not in line with expectations: we find from the statistical data that while the number of online purchases has doubled, the number of trips per person has decreased. SEM results also show that e-shopping behavior and shopping travel behavior are affected by personal attributes, family characteristics, geography, travel-related, and trip mode variables. The results could help transportation planners and policymakers understand how e-shopping and shopping trips affect each other. As a result, transportation planners are not able to alleviate traffic stress by encouraging e-shopping. In the face of the current situation of daily travel rate decline, further analysis can be carried out. Transportation planners and policymakers should also be aware of the important role that socio-demographic factors, geographic factors, and travel patterns play in e-shopping and shopping demand.

Based on previous studies, this paper makes important contributions to future travel demand management from three aspects. First, this article compares the combined statistical data and conducts subsequent model verification to prove that the increase in online shopping is not the cause of the decrease in daily trips. Secondly, the research results suggest the factors that may reduce the frequency of shopping travel demand, which can be further expanded in future travel demand management research. Third, through data integration, a unique individual variable is matched for each trip to ensure that the trip information is more accurate. Compared with other studies with limited time, budget, sample size, and survey content, this study provides the most comprehensive dataset, which can accurately and comprehensively study the interaction between online activities and flexible travel and provide an important reference for future research on travel behavior. By understanding these well, it may help set the foundations for framing better transportation policies and travel demand management strategies to serve everyone's travel needs.

Although this paper provides a perspective on the connection between ICT and travel demand for shopping, it is still subject to some limitations. Technology is constantly advancing and changing how people travel and shop whether in-store, online, or at home. Future studies on the potential impact of changes in travel behavior brought about by e-shopping on carbon dioxide emissions can be considered. In addition, NHTS only provides a limited number of variables related to this topic. In order to solve this problem, a more in-depth survey is needed to collect people's online shopping behavior. Additional studies should be conducted by expanding these travel diaries for a more in-depth look at how people shop and travel. Besides, further study could join other methods and add more variables.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

C. X. conceptualized the study, developed the methodology of the study, provided the software for the study, validated the study, carried out formal analysis of the study, wrote the original draft of the study, and did the review and edited the study; P. B. curated the data of the study; M. S. and Y. C. visualized the study; Q. W. did the project administration; Q. W. obtained funds for the study. All authors have read and agreed to the published version of the manuscript.

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References

[1] M. Castells, *The Impact of the Internet on Society: A Global Perspective*, University of Southern California, Los Angeles, CA, USA, 2019.

[2] G. Xi, X. Cao, and F. Zhen, "The impacts of same day delivery online shopping on local store shopping in Nanjing, China," *Transportation Research Part A: Policy and Practice*, vol. 136, pp. 35–47, 2020.

[3] W. Kim and X. Wang, "To be online or in-store: analysis of retail, grocery, and food shopping in New York city," *Transportation Research Part C: Emerging Technologies*, vol. 126, 2021.

[4] X. Cao, "E-shopping, spatial attributes, and personal travel," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2135, no. 1, pp. 160–169, 2009.

[5] H. Le, "Online shopping behavior of US travelers: the roles of internet usage and lifestyle, TR circular E-C238," in *Proceedings of the 2018 National Household Travel Survey Workshop*, Washington, DC, USA, August 2018.

[6] L. W. Hiselius, L. S. Rosqvist, and E. Adell, "Travel behaviour of online shoppers in Sweden," *Transport and Telecommunication Journal*, vol. 16, no. 1, pp. 21–30, 2015.

[7] S. Farag, T. Schwanen, M. Dijst, and J. Faber, "Shopping online and/or in-store? A structural equation model of the relationships between e-shopping and in-store shopping," *Transportation Research Part A: Policy and Practice*, vol. 41, no. 2, pp. 125–141, 2007.

[8] X. J. Cao, Z. Xu, and F. Douma, "The interactions between e-shopping and traditional in-store shopping: an application

of structural equations model," *Transportation*, vol. 39, no. 5, pp. 957–974, 2012.

[9] R. J. Lee, I. N. Sener, P. L. Mokhtarian, and S. L. Handy, "Relationships between the online and in-store shopping frequency of Davis, California residents," *Transportation Research Part A: Policy and Practice*, vol. 100, pp. 40–52, 2017.

[10] B. E. Tonn and A. Hemrick, "Impacts of the use of e-mail and the internet on personal trip-making behavior," *Social Science Computer Review*, vol. 22, no. 2, pp. 270–280, 2004.

[11] L. L. Sim and S. M. Koi, "Singapore's internet shoppers and their impact on traditional shopping patterns," *Journal of Retailing and Consumer Services*, vol. 9, no. 2, pp. 115–124, 2002.

[12] J. W. F. Weltevreden and T. V. Rietbergen, "E-shopping versus city centre shopping: the role of perceived city centre attractiveness," *Tijdschrift voor Economische en Sociale Geografie*, vol. 98, no. 1, 2007.

[13] U.S. Department of Transportation, *Transportation Statistics Annual Report*, U.S. Department of Transportation, Washington, DC, USA, 2018.

[14] U.S. Department of Transportation, *Changes in Online Shopping Trends*, U.S. Department of Transportation, 2018.

[15] M. C. Daniel Chatman, P. Coleman, D. Jenkins et al., "Transportation research circular," in *Proceedings of the 2018 National Household Travel Survey Workshop*, Washington, DC, USA, 2018.

[16] P. L. Mokhtarian, "A typology of relationships between telecommunications and transportation," *Transportation Research Part A: General*, vol. 24, no. 3, pp. 231–242, 1990.

[17] I. Salomon, "Telecommunications and travel relationships: a review," *Transportation Research Part A: General*, vol. 20, no. 3, pp. 223–238, 1986.

[18] European Conference of Ministers of Transport, *Transport and Telecommunications*, European Conference of Ministers of Transport, Paris, France, 1983.

[19] A. Aguiléra, C. Guillot, and A. Rallet, "Mobile ICTs and physical mobility: review and research agenda," *Transportation Research Part A: Policy and Practice*, vol. 46, no. 4, pp. 664–672, 2012.

[20] J. Casas, J. Zmud, and S. Bricka, "Impact of shopping via internet on travel for shopping purposes," in *Proceedings of the 80th Annual Meeting of the Transportation Research Board*, Washington, DC, USA, 2001.

[21] R. J. Hjorthol, "The relation between daily travel and use of the home computer," *Transportation Research Part A: Policy and Practice*, vol. 36, no. 5, pp. 437–452, 2002.

[22] G. Clarke, C. Thompson, and M. Birkin, "The emerging geography of e-commerce in British retailing," *Regional Studies, Regional Science*, vol. 2, no. 1, pp. 371–391, 2015.

[23] J. W. J. Weltevreden, "Substitution or complementarity? How the internet changes city centre shopping," *Journal of Retailing and Consumer Services*, vol. 14, no. 3, pp. 192–207, 2007.

[24] A. Schafer, "The global demand for motorized mobility," *Transport Research Part A*, vol. 32, pp. 455–477, 1999.

[25] G. Lyons and J. Urry, "Travel time use in the information age," *Transportation Research Part A: Policy and Practice*, vol. 39, no. 2-3, pp. 257–276, 2005.

[26] J. Gould and T. F. Golob, "Will electronic home shopping reduce travel?" *Access*, vol. 1, no. 12, pp. 26–31, 1998.

[27] M. Z. Irawan and E. Wirza, "Understanding the effect of online shopping behavior on shopping travel demand through strutural equation modeling," *Journal of the Eastern Asia Society for Transportation Studies*, vol. 11, pp. 614–625, 2015.

[28] S. Farag, T. Schwanen, and M. Dijst, "Empirical investigation of online searching and buying and their relationship to shopping trips," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1926, no. 1, pp. 242–251, 2005.

[29] X. Cao, F. Douma, and F. Cleaveland, "Influence of e-shopping on shopping travel," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2157, no. 1, pp. 147–154, 2010.

[30] B. I. Salomon, "Telecommunications and travel: substitution or modified mobility," *Journal of Transport Economics and Policy*, vol. 9, no. 3, pp. 219–235, 1985.

[31] S. Farag, K. J. Krizek, and M. Dijst, "E-shopping and its relationship with in-store shopping: empirical evidence from the Netherlands and the USA," *Transport Reviews*, vol. 26, no. 1, pp. 43–61, 2007.

[32] Y. Zhou and X. Wang, "Explore the relationship between online shopping and shopping trips: an analysis with the 2009 NHTS data," *Transportation Research Part A: Policy and Practice*, vol. 70, pp. 1–9, 2014.

[33] Y. Ding and H. Lu, "The interactions between online shopping and personal activity travel behavior: an analysis with a GPS-based activity travel diary," *Transportation*, vol. 44, no. 2, pp. 311–324, 2015.

[34] O. Rotem-Mindali and J. W. J. Weltevreden, "Transport effects of e-commerce what can be learned after years of research," *Transportation*, vol. 40, pp. 867–885, 2013.

[35] C. E. Ferrell, "Home-based teleshopping and shopping travel-where do people find the time?" *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1926, no. 1, 2005.

[36] E. Karadag, "Basic features of structural equation modeling and path analysis with its place and importance in educational research methodology," *Bulgarian Journal of Science and Education Policy (BJSEP)*, vol. 6, 2012.

[37] A. Edrisi and H. Ganjipour, "The interaction between e-shopping and shopping trip, Tehran," *Proceedings of the Institution of Civil Engineers - Municipal Engineer*, vol. 170, no. 4, pp. 239–246, 2017.

[38] T. F. Golob, "Structural equation modeling for travel behavior research," *Transportation Research Part B: Methodological*, vol. 37, no. 1, pp. 1–25, 2003.

[39] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, 1981.

[40] L.-T. Hu, P. M. Bentler, and Y. Kano, "Can test statistics in covariance structure analysis be trusted?" *Psychological Bulletin*, vol. 112, no. 2, pp. 351–362, 1992.

[41] J. C. Anderson and D. W. Gerbing, "Structural equation modeling in practice: a review and recommended two-step approach," *Psychological Bulletin*, vol. 103, no. 3, pp. 411–423, 1988.

[42] Federal Highway Administration, *2017 NHTS Data User Guide*, Federal Highway Administration, Washington, DC, USA, 2018.

[43] N. C. McDonald, "Critical factors for active transportation to school among low-income and minority students," *American Journal of Preventive Medicine*, vol. 34, no. 4, pp. 341–344, 2008.

[44] M. Conway, D. Salon, and D. King, "Trends in taxi use and the advent of ridehailing, 1995–2017: evidence from the US

national household travel survey," *Urban Science*, vol. 2, no. 3, 2018.
[45] D. V. Collia, J. Sharp, and L. Giesbrecht, "The 2001 national household travel survey: a look into the travel patterns of older Americans," *Journal of Safety Research*, vol. 34, no. 4, pp. 461–470, 2003.
[46] J. Pucher, R. Buehler, D. Merom, and A. Bauman, "Walking and cycling in the United States, 2001–2009: evidence from the national household travel surveys," *American Journal of Public Health*, vol. 101, no. 1, pp. S310–S317, 2011.
[47] Federal Highway Administration Office of Policy Information, *2017 NHTS Data User Guide*, Federal Highway Administration Office of Policy Information, Washington, DC, USA, 2018.
[48] H. M. Karin Schermelleh-Engel and H. Müller, "Evaluating the fit of structural equation models: tests of significance and descriptive goodness-of-fit measures," *Methods of Psychological Research*, vol. 8, pp. 23–74, 2003.
[49] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis*, Prentice Hall, Hoboken, NJ, USA, 2010.
[50] K. Maat and R. Konings, "Accessibility or innovation store shopping trips versus online shopping," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2672, no. 50, 2018.
[51] S. Farag, J. Weltevreden, T. van Rietbergen, M. Dijst, and F. van Oort, "E-shopping in the Netherlands: does geography matter?" *Environment and Planning B: Planning and Design*, vol. 33, no. 1, pp. 59–74, 2016.
[52] G. De Blasio, "Urban-rural differences in internet usage, e-commerce, and e-banking: evidence from Italy," *Growth and Change*, vol. 39, no. 2, pp. 341–367, 2008.
[53] X. Cao, Q. Chen, and S. Choo, "Geographic distribution of e-shopping," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2383, no. 1, pp. 18–26, 2013.
[54] G. Xi, F. Zhen, X. Cao, and F. Xu, "The interaction between e-shopping and store shopping: empirical evidence from Nanjing, China," *Transportation Letters*, vol. 12, no. 3, pp. 157–165, 2018.
[55] A. M. Degeratu, A. Rangaswamy, and J. Wu, "Consumer choice behavior in online and traditional supermarkets: the effects of brand name, price, and other search attributes," *International Journal of Research in Marketing*, vol. 17, no. 1, pp. 55–78, 2000.