

1 How does purchasing intangible services online influence the
2 travel to consume these services? A focus on a Chinese context

3 **Abstract:** A considerable number of empirical studies have explored the effects of information
4 & communication technologies (ICT) on travel in recent years. In particular, the most attention
5 has been paid to whether the use of ICT increases or decreases trip frequency (i.e., substitution
6 or complementarity effects). However, the subject of whether or how travel distance and mode
7 choice are altered by ICT (i.e., modification effects) has almost been ignored. Against this
8 background, using data collected in Beijing, China, this paper aims to explore how purchasing
9 intangible services (e.g., eating out at restaurants, hairdressing, and visits to zoos and movie
10 theatres) online alters the distance and mode choice of the travel to consume these services. The
11 results suggest that due to online purchases of intangible services, people tend to travel farther
12 to consume these services. Consequently, 25.4% of online buyers change their travel mode
13 choices from walking or cycling (i.e., nonmotorized modes) to public transit, private cars, or
14 taxis (i.e., motorized modes). These findings confirm the existence of modification effects of
15 ICT on travel. Additionally, a stepwise multinomial logistic regression model and a stepwise
16 binomial logistic regression model are used to detect the factors influencing changes in travel
17 distance and mode choices, respectively. The regression outcomes suggest that people who have
18 lower living costs or feel more satisfied with online purchases are more likely to increase their
19 travel distances and to change from nonmotorized modes to motorized modes.

20 **Keywords:** ICT; online purchases; intangible services; travel distance; travel mode choice;
21 China

22 **Highlights:**

- 23 (1) The modification effect of ICT on travel is examined, focusing on purchases of intangible
24 services online;
25 (2) Online purchases of intangible services increase travel distance;
26 (3) Online purchases of intangible services increase consumers' use of motorized travel modes.

27

28 **1. Introduction**

29 Information & communication technologies (ICT), which may profoundly affect travel, have
30 important implications for urban transportation systems (Gössling 2018; Mokhtarian et al. 2006;
31 Wang and Law 2007). In earlier conceptual research, four types of ICT impacts on travel were
32 proposed (Mokhtarian 1990, 2002; Salomon 1985, 1986): (1) substitution – the use of ICT
33 decreases the frequency of travel; (2) complementarity – the use of ICT increases the frequency of
34 travel; (3) modification – the characteristics of travel, such as changes in destination (and its
35 consequences for travel route and distance) and mode choice, are altered due to the use of ICT;
36 and (4) neutrality – the effects of ICT on travel are negligible. To date, a considerable number of
37 empirical studies have fully examined whether travel demand is replaced (i.e., substitution effect)
38 or generated (i.e., complementarity effect) by the use of ICT (mostly focusing on e-shopping and
39 teleworking) (e.g., e Silva and Melo 2018a,b; Shabanpour et al. 2018; Shi et al. 2019; Weltevreden
40 and Rotem-Mindali 2009; Xi et al. 2020). However, these studies leave the modification effect
41 underexamined.

42 Notably, a change in travel destination (i.e., a modification effect) due to the use of ICT could
43 constitute either substitution or complementarity, depending on whether new travel is shorter or
44 longer than previous travel (Mokhtarian 2002). More importantly, the travel mode could possibly
45 be altered once the one-way distance (i.e., distances from origins to destinations) changes due to
46 ICT since this one-way distance is strongly associated with travel mode choices (Ding et al. 2017).
47 Therefore, an investigation into modification effects (especially on travel distance and mode
48 choice) has valuable implications for urban transportation systems (e.g., congestion levels).

49 Clark and Unwin (1981) noted that travel for some purposes, such as participating in recreational
50 activities and consuming intangible services (e.g., hairdressing), cannot be replaced by online
51 activities. However, the unavoidable travel may be modifiable because of the use of ICT. As a
52 frequent ICT-based activity, searching and paying for intangible services via the internet (i.e.,
53 online purchases of intangible services) may alter one-way distances and travel mode choices to
54 consume these services. When purchasing these services online, people can extend their search
55 spaces to become aware of service information that they were unaware of before. Consequently,
56 they may travel longer distances and increase the use of motorized transportation modes.

57 In recent years, China has become the largest e-retailing market in the world (McKinsey Company
58 2016). It is reported that e-retail sales in China were ¥ 4.7 trillion (≈US\$ 0.70 trillion, and ≈EUR
59 0.62 trillion) in 2016, approximately 80% more than in the United States (IRResearch 2017b).
60 Chinese consumers very frequently purchase intangible services online. For instance, online sales
61 of intangible services in China were up 56.8% in 2016 (compared to sales in 2015) to ¥ 612.4
62 billion (≈US \$ 91.3 billion, and ≈EUR 80.9 billion) (IRResearch 2017a). In this context, using data
63 drawn from structured interviews (714 valid records) conducted in 2015 in Beijing, China, this
64 study aims to answer the following questions: 1) Do online purchases of intangible services
65 increase or decrease the one-way distances of the travel to consume these services, and if so, what
66 are the determinants of the changes in travel distances? 2) Correspondingly, is travel mode choice
67 altered by online purchases of these services, and if so, what are the determinants of the changes

68 in travel mode choice? The remainder of this paper is organized as follows. A literature review is
69 offered in the next section. Section 3 presents the methodology. Section 4 contains the results,
70 followed by a conclusion and discussion in the final section.

71 **2. Literature review**

72 2.1 Effects of ICT on travel

73 With respect to the topic of how ICT affects travel, four effects – substitution, complementarity,
74 neutrality, and modification – have been theoretically proposed in earlier work (Mokhtarian 1990,
75 2002; Salomon 1985, 1986). In the past two decades, continuously increasing empirical attention
76 has been paid to the topic.

77 Mainly focusing on online shopping and teleworking, previous empirical studies have frequently
78 confirmed the existence of substitution and complementarity effects. For instance, some studies
79 show that online shopping leads to a reduction in shopping travel frequency (Shi et al. 2019;
80 Weltevreden 2007; Xi et al. 2020) and in the distances traveled for shopping during a given period
81 (Weltevreden and Rotem-Mindali 2009). Similarly, some researchers found that teleworking via
82 the internet likely results in a decrease in total (commuting) travel distances or durations during a
83 given period (Melo and e Silva 2017; Shabanpour et al. 2018). These findings support the
84 substitution effect. In contrast, other research supports the complementarity effect because it finds
85 that frequent e-shoppers shop at physical stores more frequently (Ding and Lu 2017; Zhen et al.
86 2016), and teleworkers make more frequent trips for other purposes (Budnitz et al. 2020) and
87 travel longer total distances during a given period (e Silva and Melo 2018a,b; Melo and e Silva
88 2017). In addition to online shopping and teleworking, Wang and Law (2007) found that the
89 general use of ICT increases the durations of outdoor recreational activities and travel. Notably,
90 these studies on e-shopping often do not confirm an increase or reduction in overall travel due to
91 online shopping (i.e., a net complementarity or substitution effect). Moreover, some research
92 reveals that the use of ICT (e.g., making online purchases) has a negligible effect on travel
93 frequency, confirming the neutrality effect (Calderwood and Freathy 2014; Sim and Koi 2002).

94 Compared to the complementarity and substitution effects, far less attention has been paid to the
95 modification effect of ICT on travel. Several conceptual studies propose that ICT may potentially
96 alter travel characteristics, such as route, mode choice, and timing (Mokhtarian 1990, 2002;
97 Pawlak et al. 2015; Salomon 1985, 1986). Changes in travel destination (and its consequences for
98 travel distance) and mode choice are particularly relevant for transportation systems. However,
99 quite limited empirical research has investigated this topic. One of the exceptions is the work by
100 Farag et al. (2006, 2007), suggesting that online shopping has a modification effect on shopping
101 travel. They revealed that the frequency of e-shopping has a negative effect on the duration of
102 visiting physical stores (excluding the time of the shopping trip). However, it remains unknown
103 whether the transportation system benefits or suffers from modification effects because the authors
104 did not find changes in the duration of the shopping trip caused by e-shopping. More importantly,
105 the effects of ICT on travel mode choice have been mostly ignored in existing empirical studies.

106 The present study focuses on online purchases of intangible services and their modification effects

107 on the travel to consume these services. First of all, online purchases of intangible services need to
108 be clearly defined. It is widely accepted that e-shopping refers to the use of the internet to acquire
109 product information or purchase products (Mokhtarian 2004). In addition, online products are
110 regularly categorized into two groups. The first group is tangible goods or physical goods, such as
111 books, clothing, and groceries (Francis and White 2004; Keisidou et al. 2011). The second group
112 is intangible services, including dining-out services, travel services, and ticket services (Francis
113 and White 2004; Keisidou et al. 2011; Rushton and Carson 1989). Rigorously speaking, buying
114 intangible services is not included in regular shopping activities. Therefore, the object of the
115 present study – the internet-based purchases of intangible services – is named online purchases of
116 intangible services.

117 A plausible assumption on the modification effects of purchasing intangible services online can be
118 proposed. In general, intangible services are sold in a different way than tangible goods online.
119 Information about local intangible services is normally published on e-retail websites (e.g.,
120 Meituan.com and Nuomi.com in China and Tripadvisor.com elsewhere). Consumers can search
121 for information and pay for these services online. Afterward, they visit physical stores or places to
122 consume the services because these services are usually non-transportable (Shi et al. 2020). In this
123 case, e-buyers are less spatially constrained since they can acquire service information on more
124 distant places online that conventional buyers are unaware of. Consequently, compared to
125 conventional buyers, e-buyers are expected to make trips that are longer in distance (i.e., exhibit
126 the modification effect) after browsing and paying for services online. More importantly, this
127 might further lead to an increase in the use of motorized transportation modes.

128 2.2 Factors influencing travel distance and mode choice

129 The modification effects of ICT on travel distance and mode choice might be affected by a wide
130 range of factors. Therefore, it is worthwhile to identify these factors. However, we are unaware of
131 any previous empirical study on this issue. A number of previous studies have analyzed the factors
132 affecting travel distance and mode choice independent of ICT usage. Notably, the present study
133 specifically concentrates on the one-way distance and mode choice of the travel to consume
134 intangible services, which can broadly be categorized as nonwork travel. Therefore, we will
135 primarily review previous studies on determinants of one-way distance and mode choice of
136 nonwork travel.

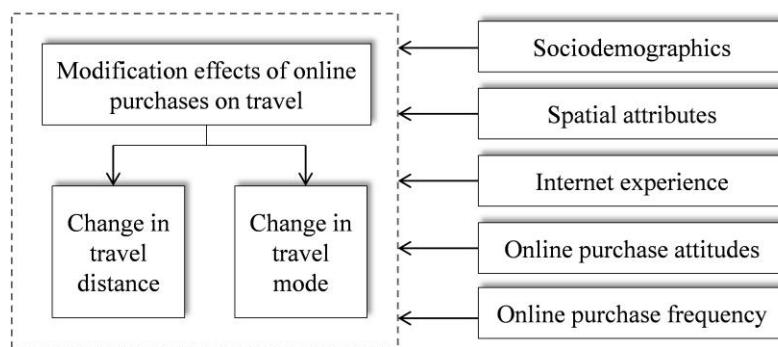
137 Sociodemographic characteristics are most frequently considered to be explanatory factors of
138 one-way distance and mode choice of nonwork travel. For example, previous studies reveal that
139 men and those with higher incomes tend to use private cars and travel longer distances per trip
140 (Chen 2017; Cheng et al., 2019b; Ding et al. 2017; Hu et al. 2018; Yang et al. 2013), partly
141 because they like driving and can afford a car. In contrast, those who are better educated are likely
142 to make shorter-distance trips than those with lower education (Chen 2017), though they prefer to
143 use private cars (Yang et al. 2013). This may be attributable to the higher perceived value of travel
144 time for them (Chen 2017).

145 Spatial attributes are regularly treated as explanatory factors for travel distance and mode choice
146 as well. In general, compared to people living in highly urbanized areas, those living in weakly
147 urbanized areas tend to travel by cars and make long-distance trips for nonwork activities (e.g.,

148 shopping and leisure activities) (Cheng et al., 2019a; De Vos and Witlox 2016; Jiao et al. 2016;
149 Scheiner and Holz-Rau 2013). This is mostly the consequence of lower accessibility to
150 opportunities in weakly urbanized areas (Scheiner and Holz-Rau 2013), an idea supported by
151 existing research. For instance, Ding et al. (2017) found that people with lower accessibility to the
152 nearest bus stop are inclined to travel farther and use private cars. Similarly, Jiao et al. (2011)
153 indicated that people who live far from grocery stores tend to drive a car to stores.

154 According to the abovementioned studies, we can reasonably assume that sociodemographics and
155 spatial attributes may relate to the changes in travel distances and mode choices caused by online
156 purchases of intangible services. In addition to the two categories of factors that are regularly
157 considered, some factors in relation to internet use may influence changes in travel behavior due
158 to online purchases as well. First, a history of internet use and attitudes toward online purchases
159 can influence the frequency of online searching for products/services (Farag et al. 2007) and thus
160 possibly relate to the one-way distances and mode choices of the travel to consume services
161 purchased online. Second, in principle, the frequency of online purchases of intangible services
162 may influence changes in travel distances and mode choices resulting from purchasing online. For
163 instance, people with frequent online purchases of intangible services must travel frequently to
164 consume them. To reduce the total distances traveled for these services, they may tend to travel
165 shorter distances per trip and thus alter their travel mode choices.

166 Given the existing knowledge gaps in relation to modification effects and their determinants, this
167 study aims to achieve the following two objectives. First, using empirical evidence from China,
168 we aim to verify whether purchasing intangible services online increases the one-way distance of
169 the travel to consume these services and, more importantly, whether the use of motorized modes is
170 facilitated due to online purchases. Second, according to previous empirical studies, it can be
171 assumed that factors such as sociodemographic characteristics, spatial attributes, internet
172 experience, online purchase frequency and attitudes may influence travel behavior. In this study,
173 regarding these factors as explanatory factors, we aim to detect which factors influence changes in
174 travel distance and mode choice due to online purchases (see Fig 1).



175

176

Fig 1 Research framework

177 **3. Methodology**

178 3.1 Data collection

179 In this study, the data are drawn from structured interviews performed in Beijing, China, by the
180 Urban and Regional Planning (URP) research group of Lanzhou University. Before conducting
181 these interviews, the URP research group selected sample units using a cluster sampling approach
182 in the following four steps (Daniel 2012). First, the target population was defined. In theory,
183 people who have at any point made a purchase online should be defined as the target population in
184 studies on e-shopping's effects on shopping travel (Rotem-Mindali and Weltevreden 2013; Shi et
185 al. 2019; Sim and Koi 2002; Weltevreden and Rietbergen 2007). Since the focus of this study is
186 online purchases of intangible services, the target population in this study is defined as anyone
187 who has ever made a purchase online for intangible services. Second, given budgetary constraints,
188 the desired sample size was finally determined to be 600-1000 so that the data can be collected
189 with sufficient confidence. Third, the sample area was chosen as the built-up area within the fifth
190 ring road of Beijing, where most residents live.

191 Fourth, the sample units were determined. Ideally, residential neighborhoods would be selected as
192 sample units to recruit participants. Researchers from the URP research group first attempted to
193 conduct the survey in residential neighborhoods. However, they did not succeed because most
194 residential neighborhoods are tightly blocked to protect the privacy of the residents in Beijing.
195 This situation is not unusual in China's large cities and has been reported in some Chinese studies
196 (e.g., Sun et al., 2017). According to the Chinese study by Sun et al. (2017) and based on the
197 principle of the cluster sampling approach (Daniel 2012; Shi et al. 2019), another alternative is to
198 perform a survey in public spaces such as shopping centers, parks, and squares when it is
199 impossible to recruit participants in residential neighborhoods. As public spaces, shopping centers
200 are the destinations of most trips to consume intangible services purchased online since intangible
201 services are densely concentrated there. Hence, shopping centers are desirable alternatives for
202 conducting interviews. Moreover, it is essential to ensure that participants are from each part of
203 the city since spatial attributes might affect online purchasing behavior. Therefore, city-level
204 shopping centers serving residents across the whole city should be randomly geographically
205 chosen as potential sample units in this survey. In the end, seven city-level shopping centers were
206 selected: Guomao Shopping Center, Xin'ao Shopping Center, Xidan Shopping Center, Wangfujing
207 Shopping Center, Zhuozhan Shopping Center, Xinzhongguan Shopping Center, and Kaide-Mall
208 Shopping Center in Wangjing (Fig 2). As a result, however, e-buyers for intangible services who
209 do not frequently go to these city-level shopping centers might be underrepresented.

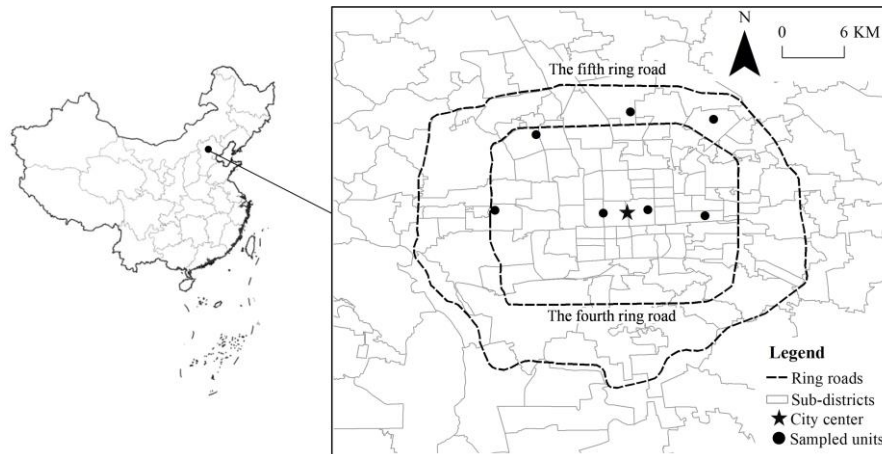


Fig 2 Spatial distribution of sampled units

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212 After determining the sample units, researchers from the URP research group conducted
 213 face-to-face structured interviews using paper-based questionnaires in October and November
 214 2015. To ensure the quality of the data, all interviewers had been trained before the interviews
 215 started. In the end, using the convenience sampling method (Etikan et al. 2016), approximately
 216 2300 residents were approached, of which 800 participated in this survey. Consequently, the
 217 response rate was approximately 35%. After the removal of questionnaires missing key
 218 information, 714 valid records were obtained. The basic characteristics of valid participants are
 219 shown in Table 1.

220

Table 1 Basic characteristics of valid respondents

Characteristics	Definitions	Percentage
Gender	Male	39.1%
	Female	60.9%
Age (Years)	20 or less (Value=1)	10.5%
	21-25 (Value=2)	41.0%
	26-30 (Value=3)	28.4%
	more than 30 (Value=4)	20.0%
Education	High school or less (Value=1)	7.3%
	Colleges and technical school (Value=2)	17.6%
	Undergraduate school (Value=3)	52.8%
	Graduate school or more (Value=4)	22.3%
Income (¥/month)	2000 or less (Value=1)	19.0%
	2001-6000 (Value=2)	32.6%
	6001-10000 (Value=3)	29.6%
	More than 10000 (Value=4)	18.8%
Cost of living (¥/month)	1000 or less (Value=1)	8.7%
	1001-3000 (Value=2)	45.0%
	3001-5000 (Value=3)	27.5%
	More than 5000 (Value=4)	18.9%
Years of using the internet on PCs	5 or less (Value=1)	10.1%
	6-9 (Value=2)	36.4%
	More than 9 (Value=3)	53.5%
Departure location	Urban area	52.4%
	Suburban area	25.9%
	Exurban area	21.7%

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According to the report by the China Electronic Commerce Research Center (2016), 47.4% of e-shoppers in 2016 in China were men, and 48.8% were more than 26 years old. Of the 714 valid participants, 39.1% were men, and 48.4% were 26 years old or older. Participants in this study could be considered representative with respect to broad age classifications, while a possible

225 selection bias in terms of gender is observed. This may be due to the following reasons. (1) As
226 stated before, e-buyers are defined in this study as those who have ever purchased intangible
227 services online. In contrast, the China Electronic Commerce Research Center (2016) defines
228 e-shoppers as those who have ever made a purchase online (including both tangible goods and
229 intangible services). (2) China has a vast territory with considerable regional differentiation in the
230 socioeconomic attributes of residents. Therefore, it seems reasonable that the sociodemographic
231 characteristics of e-purchases in Beijing are somewhat different from those across the whole
232 country. It should be noted that we are not aware of any other reports concerning e-shoppers in
233 Beijing or e-buyers for intangible services in China in 2015. Hence, it is impossible to compare
234 the attributes of the respondents with a more accurate report on the e-purchasing population of
235 China or Beijing. (3) In this survey, shopping centers were chosen as the sample units. Compared
236 to men, women visit shopping centers more frequently in China (e.g., Feng et al. 2015). As a result,
237 the valid respondents might overrepresent women to a certain degree. Beyond age and gender,
238 they are of unknown representativeness regarding other attributes.

239 3.2 Method of analysis

240 3.2.1 Measurement of changes in travel distance and mode choice

241 Four categories of intangible services that are most frequently purchased online in China were
242 selected for this study. The first category refers to daily life services, including hairdressing visits
243 and photography services. The second category is dining-out services, which refers to going out to
244 eat food at restaurants, snack and dessert stores, etc. The third category is leisure services,
245 including visits to movie theatres, (karaoke) bars, and fitness services. The last category refers to
246 local tourism, such as visits to zoos, theme parks, museums, and resorts.

247 In China, most online buyers tend to combine both online and conventional purchases for
248 intangible services. For example, sometimes an online buyer browses and orders food online
249 before going to a restaurant to consume it (i.e., uses the online channel). At times, however, he/she
250 also directly goes to the restaurant without searching and ordering online beforehand (i.e., uses the
251 conventional channel). In this context, only the respondents who used both channels were asked
252 two questions: In the recent past, 1) how far away was your most visited place for consuming
253 intangible services when adopting the online channel? 2) How far away was your most visited
254 place for consuming intangible services when adopting the conventional channel? Thus, the
255 self-reported travel distance was obtained in this survey. Noting the differences among these types
256 of intangible services, the respondents were asked to provide information about the travel distance
257 for the four categories of intangible services separately. Not every respondent purchased all four
258 types of services using both online and conventional channels. Participants who purchased at
259 least one type of these services using both channels were included as valid respondents.

260 By comparing travel distance for the online channel and the conventional channel reported by
261 each respondent, we can determine whether he/she increased or decreased his/her travel distance
262 due to online purchases of intangible services. For example, if a respondent indicated a longer
263 distance for the online channel than for the conventional channel, it suggests that his/her travel
264 distance was increased by online purchases. In contrast, if a respondent reported a shorter distance

265 for the online channel than for the conventional channel, it can be assumed that his/her travel
266 distance decreased due to online purchases. Additionally, if a respondent indicated that his/her
267 travel distance for the online channel was not significantly different from that for the conventional
268 channel, we consider online purchases to have had a negligible effect on travel distance.

269 It may be argued that it was not easy for participants to accurately recall the distances of their
270 typical trips, resulting in a possible recall bias. Nevertheless, the quality of the data in this study is
271 credible for two reasons. First, respondents were asked to provide the most visited location for
272 intangible services beforehand. It then became easier for them to estimate the travel distance. This
273 is the value of face-to-face interviews. Second, the focus of this study is not to accurately estimate
274 the distance traveled by online buyers. We aim to focus on whether travel distance increases due to
275 online purchases and, more importantly, whether a greater use of motorized travel modes results
276 from an increase in travel distance. A number of previous studies have suggested that the
277 self-reported distance of a single trip is strongly associated with travel mode choice (e.g.,
278 Mehdizadeh et al. 2017; Piatkowski and Marshall 2015). Nelson et al. (2008) even postulated that,
279 compared to the actual distance, the self-reported distance might be more related to travel mode
280 choice. Hence, it could be assumed that using the self-reported distance was suitable in this study.

281 Following the method frequently used in previous studies (e.g., Barata et al. 2011; Duarte et al.
282 2016; Heinen et al. 2011; Motoaki and Daziano 2015), two questions were set in the questionnaire
283 for travel mode choice: In the recent past, 1) which transport mode did you use the most to travel
284 to consume an intangible service ordered online? 2) Which transport mode did you use the most to
285 travel to consume an intangible service without an online order? Three answers to the two
286 questions were set as options: private car or taxi, public transit (e.g., bus, metro), and walking or
287 cycling. Thus, we were able to determine changes in travel mode choice due to online purchases.
288 One should note that the questions concerning mode choices were not asked separately for the
289 four categories of intangible services.

290 3.2.2 Measurement of explanatory factors

291 As shown in Fig 1, the explanatory factors can be grouped into five categories. The first category
292 includes sociodemographic characteristics, which consist of gender, age, income, education, and
293 cost of living. Age, education, income, and cost of living are measured by ordinal scales. The
294 values assigned to them are shown in Table 1.

295 The second category refers to spatial attributes. In previous studies, most scholars have used
296 residential location to reflect spatial attributes (e.g., De Vos and Witlox 2016; Jiao et al. 2016).
297 Notably, using residential location as a spatial attribute might have shortcomings. For instance, it
298 is normally expected that compared to people living in urban areas, those living in suburban areas
299 have lower accessibility to activity places (e.g., stores) and thus usually travel longer distances per
300 trip. However, there may be a trip chain. For example, a person living in a suburban area and
301 working in an urban area is more likely to visit activity places on the way home from the
302 workplace because of the workplace's higher accessibility to these places. In this circumstance,
303 this person is expected to travel a shorter distance even though he/she lives in a suburban area.
304 Therefore, one-way distance is influenced not only by residential location but also mainly by
305 departure location (which might differ from residential location). In this study, we therefore use

306 the location where respondents mostly depart for trips to consume intangible services as a spatial
 307 attribute. Considering that the degree of urbanization continuously decreases from the city center
 308 to the city fringes in Beijing, urban areas, suburban areas, and exurban areas are bounded by the
 309 fourth and fifth ring roads, respectively, in a number of empirical studies (e.g., Mao et al. 2016; Li
 310 et al. 2019; Lin et al. 2018; Wang et al. 2015; Zhao and Li 2017; Zhao and Zhang 2018).
 311 Following these previous studies, we define the areas within the fourth ring road as urban areas,
 312 the areas between the fourth ring road and the fifth ring road as suburban areas, and the areas
 313 outside the fifth ring road as exurban areas (Fig 2). Thus, of 714 valid records in the study, 52.4%,
 314 25.9%, and 21.7% mostly depart for trips from urban areas, suburban areas, and exurban areas,
 315 respectively (see Table 1).

316 The third explanatory category is internet experience, which is reflected by the number of years
 317 using the internet on PCs (the assigned values are shown in Table 1). The fourth category refers to
 318 online purchasing behavior. The respondents were asked to provide information on the average
 319 frequency of online purchases of four types of intangible services separately. Online purchasing
 320 frequency for daily life services and local tour services was measured in a regular year and that for
 321 dining-out services and leisure services was measured in a regular month. Considering that the
 322 measurement scales differ according to the type of services, the frequency values were normalized
 323 using the technique of min-max normalization. We further summed the normalized frequency
 324 values for the four types of intangible services, representing the level of total online purchase
 325 frequency. In this study, the normalized frequency values were used to reflect respondents' online
 326 purchasing behavior.

327 The final category is attitudes toward purchasing intangible services online. Respondents were
 328 asked to respond to 18 statements using a 5-point scale ranging from strongly disagree to strongly
 329 agree. Performing factor analysis (principal axis factoring, Promax rotation) obtained five factors
 330 (mainly based on eigenvalue>1.0) explaining 52.6% of the total variance: ease of travel,
 331 satisfaction, following trends, convenience, and price consciousness (see Table 2). In this paper,
 332 the scores of these five factors are used to capture respondents' attitudes toward online purchases.

333 *Table 2 Pattern matrix from factor analysis on attitudes toward online purchases (n=713)*

Factors	Statements	Loadings
Ease of travel	Online purchase is a strategy to save travel time	0.92
	Online purchase is a strategy to reduce travel distance	0.86
	The places publishing service information online are highly accessible	0.69
	I can find the sites of places providing services and plan the travel route online	0.42
Satisfaction	I usually purchase online again after first buying online	0.78
	Compared to conventional purchase, I am more satisfied with online purchase	0.68
	I am pleased to recommend online purchase to my friends and relatives	0.66
	I usually feel satisfied with online purchase	0.56
Following trends	Online purchase is a popular lifestyle choice	0.95
	Online purchase is a process that seeks novelty	0.78
	I purchase online because people around me do it (Herd behavior)	0.46
Convenience	It is convenient to select services online	0.86
	I can find a large variety of services online	0.67
	I can find high-quality services online	0.44
	I enjoy the freedom of the online purchase environment	0.43
	It is convenient to pay for services online	0.38

Price-consciousness	I enjoy the discounts by purchasing online	0.93
	The price of online services is lower	0.83

334 The “loading” reflects the relative importance of each statement in the factors.

335 3.2.3 Modeling approach

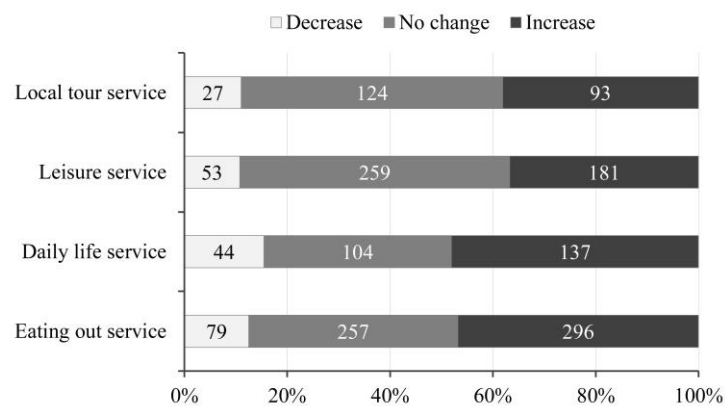
336 Using logistic regression models, we aimed to identify the determinants of changes in travel
 337 distance and mode choice due to online purchases. In these models, changes in travel distance or
 338 mode choice were employed as the dependent variable, and the five categories of explanatory
 339 factors were used as independent variables. Regarding changes in travel distance, respondents who
 340 indicated purchasing more than one type of intangible service online were included in the model
 341 more than once. In other words, one case represents the online purchase of one type of service. In
 342 this study, there were 714 respondents and 1653 observations for changes in travel distance. The
 343 service types were controlled for in the regression model concerning changes in travel distance.

344 4. Results

345 4.1 Do online purchases increase travel distance?

346 4.1.1 Changes in travel distance

347 In this section, we explore how online purchases of intangible services affect the one-way distance
 348 of the travel to consume these services. As shown in Fig 3, a considerable number of respondents
 349 reported increasing their travel distances. In particular, for daily life services and dining-out
 350 services, more than 40% of respondents indicated an increase in travel distances. However, just
 351 knowing that more e-buyers choose to increase than decrease their travel distances due to online
 352 purchases does not convey the full picture. It remains unknown whether the distances increased by
 353 online purchases are larger than the distances decreased by online purchases. Accordingly, the
 354 outcomes of the Wilcoxon signed-rank test¹ in Table 3 confirm that on average, the self-reported
 355 travel distance for the online channel is significantly longer than for the conventional channel
 356 ($p < 0.01$). It suggests that, as expected, online purchases likely stimulate online buyers to travel
 357 longer distances.



358

¹ Given that the distances are not normally distributed, the Wilcoxon signed-rank test, which is a nonparametric method, was adopted in this study.

359

Fig 3 Number of respondents who decreased, increased or did not change their travel distance

360

Table 3 Comparison of travel distance for purchases made through conventional and online channels

Type of services	Type of purchases	Travel distance (km)		Wilcoxon signed-rank test
		Mean	S.D.	
Eating out service (N=632)	Conventional channel	3.34	3.63	Z=-10.44
	Online channel	4.70	4.18	Sig.=0.00
Daily life service (N=285)	Conventional channel	3.69	3.85	Z=-6.74
	Online channel	5.13	4.50	Sig.=0.00
Leisure service (N=493)	Conventional channel	4.19	3.83	Z=-7.84
	Online channel	5.26	4.37	Sig.=0.00
Local tour service (N=244)	Conventional channel	10.02	10.70	Z=-5.60
	Online channel	12.46	11.49	Sig.=0.00

361

4.1.2 Factors influencing changes in travel distance

362

363 After respondents were categorized into three groups to indicate increasing, decreasing, or
 364 unchanged travel distances, a multinomial logistic regression model was developed to detect the
 365 factors influencing changes in travel distance (Table 4). To improve the efficiency of the
 366 estimators, the backward stepwise regression method was used to exclude the far less relevant
 367 explanatory variables. Insignificant variables with $p > 0.20$ were removed from the model because
 368 an excessively stringent threshold value (e.g., $p > 0.05$) might result in a loss of important
 369 correlates (Hosmer Jr et al. 2013). Meanwhile, the Hausman test suggests that the assumption of
 370 the independence of irrelevant alternatives was not violated by the pruned model. Additionally,
 371 cluster-robust standard errors were estimated since some respondents were included more than

372

373 Afterward, the prediction accuracy of the regression estimation was calculated to assess its validity.
 374 It is traditionally predicted that a choice-maker chooses the alternative with the highest predicted
 375 probability. The prediction accuracy is computed according to the comparison between the
 376 predicted outcomes and the actual observations. However, the method receives many critiques
 377 (e.g., Train 2009; Young and Blainey 2018). In general, researchers perform a regression
 378 estimation using partial information. Thus, they can only estimate the probability that a
 379 choice-maker chooses each of the alternatives, respectively (Train 2009). In this case, the
 380 traditional method is crudely used for prediction without any consideration of other alternatives
 381 with relatively low predicted probabilities. To overcome the limitations of the traditional measure,
 382 a better approach is introduced (McFadden 2001). The prediction accuracy for an alternative is
 383 computed as the average of the predicted probabilities for that alternative across respondents who
 384 actually chose the alternative. Similarly, by combining all alternatives, the prediction accuracy in
 385 total can be calculated. Using the latter approach, the present study computed prediction accuracy
 386 (Table 5). The prediction accuracies for the three categories (decrease, no change, and increase)
 387 are 14.77%, 47.48%, and 45.68%, respectively, resulting in a total level of 42.69%. The prediction
 388 accuracies for “no change” and “increase” are nearly acceptable, while that for “decrease” is quite
 389 low. It should be noted that prediction accuracies using the latter approach are often lower but
 390 more appropriate than those using the traditional approach (Kim and Mokhtarian 2018).

390

391 As a whole, sociodemographic characteristics, internet experience, and attitudes toward online
 purchases were found to be significantly associated with changes in travel distance ($p < 0.10$). As

392 suggested in Table 4, people who are better educated tended to increase their travel distances due
 393 to online purchases. People with lower living costs were inclined to increase their travel distances.
 394 It could be assumed that people with lower living costs care more about the price of services. Thus,
 395 they may travel a longer distance so that they can consume the services at a lower price.
 396 Additionally, people with fewer years of experience using the internet were more likely to change
 397 (either increase or decrease) their travel distances. They may have been more curious about online
 398 purchase activity than people who have used the internet for multiple years. Thus, they might have
 399 more actively searched online for stores/places situated within easy access or distantly situated to
 400 break their dependence on regularly visited stores/places. Regarding attitudes toward online
 401 purchases, people who paid more attention to the ease of travel were less likely to increase their
 402 travel distances and more likely to decrease their travel distances. This is in line with our
 403 expectations. People who felt satisfied with online purchases were more likely to change (either
 404 increase or decrease) their travel distances, which could be similarly attributed to their greater
 405 engagement in online searching. Furthermore, respondents who considered online purchases
 406 convenient were less likely to decrease their travel distances. We did not find that online purchase
 407 frequency and spatial attributes had associations with changes in travel distance at a significance
 408 level of $p < 0.10$.

409 *Table 4 Stepwise multinomial logistic regression model concerning changes in travel distance (no change=ref.)*

Independent variables	Decrease			Increase		
	B	Robust S.E.	Sig.	B	Robust S.E.	Sig.
Education	0.00	0.14	0.988	0.25	0.09	0.007
Cost of living	0.10	0.13	0.460	-0.21	0.09	0.020
Years of using the internet on PCs	-0.50	0.18	0.006	-0.33	0.12	0.007
Attitudes toward purchasing online						
Ease of travel	0.32	0.12	0.007	-0.31	0.09	0.001
Satisfaction	0.27	0.14	0.049	0.17	0.10	0.093
Convenience	-0.27	0.14	0.052	0.03	0.10	0.779
Types of services (daily life service=ref.)						
Local tour service	-0.66	0.26	0.012	-0.63	0.17	0.000
Leisure service	-0.77	0.21	0.000	-0.71	0.14	0.000
Eating out service	-0.35	0.21	0.093	-0.19	0.13	0.163
Constant	0.04	0.53	0.938	0.94	0.38	0.013
Log pseudolikelihood at zero	-1816.0					
Log pseudolikelihood at constants only	-1620.3					
Log pseudolikelihood at convergence	-1552.9					
McFadden's R^2 at constants only	0.00					
McFadden's R^2 at convergence	0.04					
Number of observations	1653					

410 *Table 5 Prediction accuracy of the stepwise multinomial logistic regression model*

Categories	Prediction accuracy (%)
Decrease	14.77
No change	47.48
Increase	45.68
Total	42.69

411 4.2 Do online purchases change the travel mode choice?

412 4.2.1 Changes in travel mode choice

413 In this section, we aim to investigate the effect of purchasing intangible services online on travel
 414 mode choice. The matrix of changes in mode choice is presented in Table 6. The results suggest

415 that a considerable share of respondents (36.3%) indicated changing their travel mode choices due
 416 to online purchases. In particular, more than a quarter of respondents indicated changing their
 417 travel mode choices from walking or cycling to using a private car, a taxi, or public transit (i.e.,
 418 changing from nonmotorized modes to motorized modes). Among the 714 valid respondents, 45
 419 (6.3%) reported changing their travel mode choice from walking or cycling to using a private car
 420 or a taxi, and 136 (19.0%) indicated changing to using public transit. Additionally, the Chi-squared
 421 test indicates that the probability that respondents used motorized modes for trips with online
 422 orders and for trips without online orders is significantly different ($\chi^2=86.2$, $p<0.01$).

423 *Table 6 Changes in travel mode choice*

		Online channel			Total
		Car/taxi	Public transit	Walking/cycling	
Conventional channel	Car/taxi	114	27	13	154
	Public transit	19	279	19	317
	Walking/cycling	45	136	62	243
	Total	178	442	94	714

424 As assumed before, trips to consume intangible services are normally unavoidable, even when
 425 purchasing online (Clark and Unwin 1981). More importantly, additional trips might be further
 426 generated by online purchases in some situations. In general, consumers can acquire massive
 427 information on goods/services online (Cao et al. 2012; Shi et al. 2019). Moreover, online
 428 goods/services usually have better prices compared to goods/services in stores (e.g., larger
 429 discounts) (Rotem-Mindali and Weltevreden, 2013). These circumstances may lead to additional
 430 online purchases and consequently more trips to consume services. To verify this expectation,
 431 following the measurement method of previous studies (e.g., Shi et al. 2019; Weltevreden 2007;
 432 Xi et al. 2020), the self-reported changes in the frequency of the travel to consume intangible
 433 services due to online purchases were obtained in the survey. The results show that of 714 valid
 434 respondents, 52.8% indicated an increase in trip frequency because of online purchases, while
 435 only 6.9% reported a decrease in frequency. Additionally, as shown in Table 7, respondents quite
 436 frequently purchased intangible services online, and trips with online orders accounted for a
 437 considerable share (45.6% to 60.6%) of their total trips to consume intangible services. These
 438 results suggest that the use of motorized modes for consuming intangible services could be
 439 considerably stimulated by purchasing online.

440 *Table 7 The frequency of trips with online orders and their shares in total trip frequency*

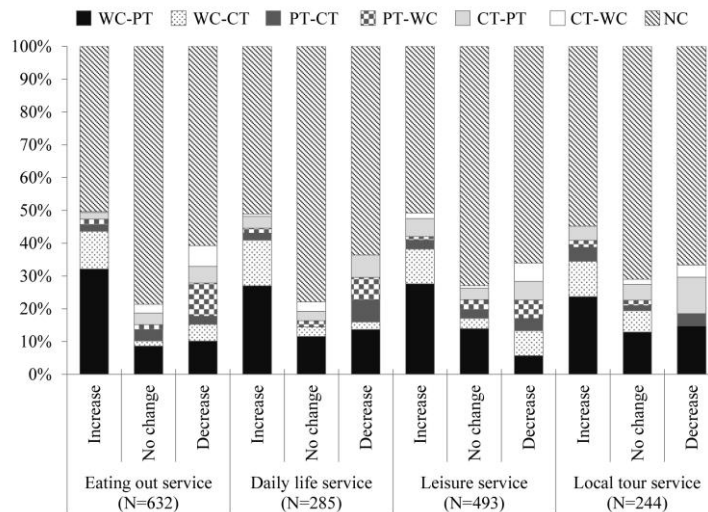
Type of services	Type of purchases	Trip frequency		Share of trips with online orders (%)	
		Mean	S.D.	Mean	S.D.
Eating out service (N=654)	Conventional channel	9.51 ^a	11.87 ^a	45.6	20.0
	Online channel	6.13 ^a	5.61 ^a		
Daily life service (N=295)	Conventional channel	16.03 ^b	25.00 ^b	46.4	19.2
	Online channel	11.47 ^b	13.58 ^b		
Leisure service (N=598)	Conventional channel	3.31 ^a	4.27 ^a	60.6	22.4
	Online channel	3.61 ^a	3.45 ^a		
Local tour service (N=271)	Conventional channel	8.86 ^b	15.59 ^b	53.5	21.0
	Online channel	8.62 ^b	12.84 ^b		

441 a - monthly frequency, b - yearly frequency;

442 Total trip frequency - the sum of the frequency of trips with online orders and without online orders.

443 By and large, changes in travel mode choice could be attributed to changes in travel distance
 444 according to Fig 4. In particular, respondents who indicated increasing travel distances were more

445 likely to change their travel mode choices from walking/cycling to public transit and car/taxi. Not
 446 surprisingly, people who reported not changing their travel distances were inclined to keep their
 447 travel mode choices constant. Additionally, those indicating a decrease in travel distances tended to
 448 change their travel mode choices from public transit or car/taxi to walking/cycling.



449

450 “WC-PT” change from walking/cycling to public transit; “WC-CT” change from walking/cycling to car/taxi;
 451 “PT-CT” change from public transit to car/taxi; “PT-WC” change from public transit to walking/cycling; “CT-PT”
 452 change from car/taxi to public transit; “CT-WC” change from car/taxi to walking/cycling; “NC” no change.

453

Fig 4 Changes in travel mode choice by changes in travel distance

454 4.2.2 Factors influencing changes in travel mode choice

455 Considering that more than one-quarter of respondents changed from nonmotorized travel modes
 456 to motorized modes due to online purchases of intangible services, we aimed to identify the
 457 determinants of that change using a binomial logistic regression model. Following Hosmer Jr et al.
 458 (2013), the backward stepwise regression method was used to exclude independent variables that
 459 were quite insignificantly associated with the dependent variables ($p > 0.20$). The outcomes are
 460 reported in Table 8. Similarly, the prediction accuracy was computed and reported in Table 9. The
 461 prediction accuracy in total reaches a reasonable level (63.44%), suggesting that, despite a
 462 relatively low pseudo R^2 , the goodness-of-fit is acceptable or nearly acceptable.

463 The outcomes suggest that people who had lower living costs, cared less about the ease of travel,
 464 or were more satisfied with online purchases were more likely to change from nonmotorized
 465 modes to motorized modes (at a significance level of $p < 0.10$). This finding is consistent with our
 466 expectations since these respondents were (more or less) likely to increase their travel distances.
 467 Additionally, gender and spatial attributes were significantly associated with the change from
 468 nonmotorized modes to motorized modes. Men were more likely to change from nonmotorized
 469 modes to motorized modes, which could be partly attributed to their higher probability of using a
 470 car in China (Yang et al. 2013). Compared to people mostly departing from weakly urbanized
 471 areas (i.e., exurban areas), those mostly departing from strongly urbanized areas (i.e., urban and
 472 suburban areas) were more likely to change from nonmotorized modes to motorized modes,
 473 probably because of their higher accessibility to public transit.

474

475

Table 8 Stepwise binomial logistic regression model concerning change in travel mode choice

Independent variables	From nonmotorized modes to motorized modes (Yes=1, No=0)		
	B	S.E.	Sig.
Gender (Female=ref.)	0.42	0.18	0.019
Cost of living	-0.26	0.10	0.010
Departure location (Exurban area=ref.)			
Urban area	0.31	0.24	0.196
Suburban area	0.56	0.26	0.032
Online purchase frequency	0.38	0.24	0.119
Attitudes toward purchasing online			
Ease of travel	-0.17	0.10	0.085
Satisfaction	0.20	0.11	0.064
Constant	-1.07	0.34	0.002
Log likelihood at zero	-494.2		
Log likelihood at constant only	-404.2		
Log likelihood at convergence	-392.1		
McFadden's R^2 at constant only	0.00		
McFadden's R^2 at convergence	0.03		
Number of observations	713		

476

Table 9 Prediction accuracy of the stepwise binomial logistic regression model

Categories	Prediction accuracy (%)
From nonmotorized modes to motorized modes (Yes)	27.88
From nonmotorized modes to motorized modes (No)	75.51
Total	63.44

477 5. Conclusion and discussion

478 With the widespread use of ICT in recent years, numerous researchers have demonstrated the
 479 effects of ICT on travel. Although it has been conceptually proposed that ICT have modification
 480 effects on travel distance and mode choice, very limited empirical evidence has been presented to
 481 support this idea. Therefore, using data drawn from a questionnaire survey in Beijing, China, this
 482 study aimed to explore the modification effects of purchasing intangible services online on travel.
 483 The results suggest that the distance of a single trip likely increases due to online purchases.
 484 Consequently, 36.3% of online purchasers indicate changes in their travel mode choices, with
 485 changes from nonmotorized modes to motorized modes being the most common (25.4%).
 486 Furthermore, using logistic regression models, the determinants of changes in travel distance and
 487 mode choice were identified. The outcomes suggest that sociodemographic characteristics, spatial
 488 attributes, internet experience, and attitudes toward online purchases are significantly associated
 489 with changes in travel distance and the change from nonmotorized modes to motorized modes.

490 Our findings have two important implications. On the one hand, this study fills research gaps from
 491 previous studies. First, we extend the knowledge of the modification effects of ICT on travel using
 492 empirical evidence from China. Our results suggest that online buyers of intangible services tend
 493 to increase the distance of trips to consume services and thus have a greater probability of using
 494 motorized travel modes. Second, we also detect the factors affecting changes in travel distance and
 495 mode choice. These findings add new knowledge to the body of existing literature.

496 On the other hand, policy makers and urban planners consequently need to cope with the new
 497 challenge brought about by purchases of intangible services online. Online purchases of intangible
 498 services seem to result in a greater use of motorized travel modes for the consumption of these
 499 services, which might be a challenge for the transportation system and might increase transport

500 CO₂ emissions. Nevertheless, since both the frequency of trips and the distance of a single trip
501 increase due to online purchases of intangible services, online buyers may reduce their time
502 budget for trips for other purposes. As a result, the use of motorized modes for other purposes
503 might be correspondingly reduced. Therefore, the net effect of online purchases of intangible
504 services on the use of motorized modes needs to be considered when policy is made. Additionally,
505 online buyers particularly change travel mode choices from walking or cycling to public transit.
506 The demand for public transit might therefore be stimulated to a certain extent.

507 Although new insights have been gathered regarding the understanding of the travel effects of ICT,
508 a few limitations exist in this study. First, a possible selection bias resulting from recruiting
509 participants at shopping centers might limit the generalizability of the findings. In particular, the
510 modification effects of purchasing intangible services online on travel might be slightly
511 overestimated because less-mobile online buyers may be underrepresented in this study. In future
512 research, the issue of selection bias needs to be addressed. Second, only the self-reported travel
513 distance was used to measure changes in travel distance due to online purchases, which limits our
514 empirical analyses in two aspects. On the one hand, we cannot analyze the factors influencing the
515 exact extent to which the one-way travel distance increased or decreased due to online purchases
516 because the self-reported distance cannot accurately represent the actual distance. On the other
517 hand, the exact total amount of the increase in travel distances due to online purchases cannot be
518 estimated in this study. In the future, by using the actual travel distance and taking trip frequency
519 into account, researchers can address these two issues. Third, with respect to regression models,
520 two improvements can be made in future research. On the one hand, due to relatively limited
521 observations, changes in mode choice are crudely classified into binary variables to be used as
522 dependent variables in the regression model. More observations are needed to derive more varied
523 dependent variables for modeling in future studies. On the other hand, the low values of the
524 pseudo R^2 suggest that a considerable share of the variance in the change in travel distance and
525 mode choice is not explained by our regression models. The outcomes of the regression models
526 may change if additional relevant variables are included. This could be regarded as an issue to be
527 addressed in future research.

528

529 **Authors' contribution**

530 K. Shi: Identification of research gaps, conceptualization, literature search and review, analysis,
531 and manuscript writing; L. Cheng, J. De Vos, and W. Cao: Conceptualization, analysis and
532 manuscript editing; Y. Yang: Identification of research gaps and manuscript editing; F. Witlox:
533 Manuscript editing and final approval of the paper.

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545

546 References

- 547 Barata, E., Cruz, L., Ferreira, J. P.: Parking at the UC campus: Problems and solutions. *Cities* 28(5), 406-413
548 (2011).
- 549 Budnitz, H., Tranos, E., Chapman, L.: Telecommuting and other trips: An English case study. *Journal of Transport*
550 *Geography* 85, 102713 (2020).
- 551 Calderwood, E., Freathy, P.: Consumer mobility in the Scottish isles: The impact of internet adoption upon retail
552 travel patterns. *Transportation Research Part A: Policy and Practice* 59(1), 192-203 (2014).
- 553 Cao, X., Xu, Z., Douma, F.: The interactions between e-shopping and traditional in-store shopping: An application
554 of structural equations model. *Transportation* 39(5), 957-974 (2012).
- 555 Chen, Y.: Neighborhood form and residents' walking and biking distance to food markets: Evidence from Beijing,
556 China. *Transport Policy*. <https://doi.org/10.1016/j.tranpol.2017.09.015> (2017).
- 557 Cheng, L., Chen, X., Yang, S., Cao, Z., De Vos, J., Witlox, F.: Active travel for active ageing in China: The role of
558 built environment. *Journal of Transport Geography* 76, 142-152 (2019a).
- 559 Cheng, L., Chen, X., Yang, S., Wu, J., Yang, M.: Structural equation models to analyze activity participation, trip
560 generation, and mode choice of low-income commuters. *Transportation Letters* 11(6), 341-349 (2019b).
- 561 China Electronic Commerce Research Center: Report of insight into online consumption of consumers and
562 guidance on e-shopping in 2016 in China. Available at: <http://www.100ec.cn/zt/16zgfxz/> (2016). Accessed 4
563 April 2019.
- 564 Clark, D., Unwin, K. I.: Telecommunications and travel: Potential impact in rural areas. *Regional Studies* 15(1),
565 47-56 (1981).
- 566 Daniel, J.: Chapter 5. Choosing the Type of Probability Sampling. *Sampling Essentials: Practical Guidelines for*
567 *Making Sampling Choices* 125-174 (2012).
- 568 De Vos, J., Witlox, F.: Do people live in urban neighbourhoods because they do not like to travel? Analysing an
569 alternative residential self-selection hypothesis. *Travel Behaviour and Society* 4, 29-39 (2016).
- 570 Ding, C., Wang, D., Liu, C., Zhang, Y., Yang, J.: Exploring the influence of built environment on travel mode
571 choice considering the mediating effects of car ownership and travel distance. *Transportation Research Part A:*
572 *Policy and Practice* 100, 65-80 (2017).
- 573 Ding, Y., Lu, H.: The interactions between online shopping and personal activity travel behavior: An analysis with
574 a GPS-based activity travel diary. *Transportation* 44(2), 311-324 (2017).
- 575 Duarte, F., Gadda, T., Luna, C. A. M., Souza, F. T.: What to expect from the future leaders of bogotá and curitiba in
576 terms of public transport: Opinions and practices among university students. *Transportation Research Part F:*
577 *Traffic Psychology and Behaviour* 38, 7-21 (2016).
- 578 e Silva, J. D. A., Melo, P. C.: Does home-based telework reduce household total travel? A path analysis using
579 single and two worker British households. *Journal of Transport Geography* 73, 148-162 (2018a).
- 580 e Silva, J. D. A., Melo, P. C.: Home telework, travel behavior, and land-use patterns. *Journal of Transport and Land*
581 *Use* 11(1), 419-441 (2018b).
- 582 Etikan, I., Musa, S. A., Alkassim, R. S.: Comparison of convenience sampling and purposive sampling. *American*
583 *Journal of Theoretical and Applied Statistics* 5(1), 1-4 (2016).
- 584 Farag, S., Krizek, K. J., Dijst, M.: E-shopping and its relationship with in-store shopping: Empirical evidence from
585 the Netherlands and the USA. *Transport Reviews* 26(1), 43-61 (2006).
- 586 Farag, S., Schwanen, T., Dijst, M., Faber, J.: Shopping online and/or in-store? A structural equation model of the
587 relationships between e-shopping and in-store shopping. *Transportation Research Part A: Policy and Practice*

588 41(2), 125-141 (2007).

589 Feng, J., Dijst, M., Wissink, B., Prillwitz, J.: Elderly co-residence and the household responsibilities hypothesis:
590 Evidence from Nanjing, China. *Urban Geography* 36(5), 757-776 (2015).

591 Francis, J. E., White, L.: Value across fulfillment-product categories of internet shopping. *Managing Service*
592 *Quality: An International Journal* 14(2/3), 226-234 (2004).

593 Gössling, S.: ICT and transport behavior: A conceptual review. *International Journal of Sustainable*
594 *Transportation* 12(3), 153-164 (2018).

595 Heinen, E., Maat, K., Van Wee, B.: The role of attitudes toward characteristics of bicycle commuting on the choice
596 to cycle to work over various distances. *Transportation Research Part D: Transport and Environment* 16(2),
597 102-109 (2011).

598 Hosmer Jr, D. W., Lemeshow, S., Sturdivant, R. X.: *Applied Logistic Regression*. John Wiley & Sons (2013).

599 Hu, H., Xu, J., Shen, Q., Shi, F., Chen, Y.: Travel mode choices in small cities of China: A case study of
600 Changting. *Transportation Research Part D: Transport and Environment* 59, 361-374 (2018).

601 IResearch: Report of O2O e-commerce serving local life in 2017 in China. Available at:
602 <http://report.iresearch.cn/report/201707/3024.shtml> (2017a). Accessed 20 January 2019.

603 IResearch: The changing face of China online retailing. Available at:
604 <http://report.iresearch.cn/report/201711/3083.shtml> (2017b). Accessed 20 January 2019.

605 Jiao, J., Moudon, A. V., Drewnowski, A.: Does urban form influence grocery shopping frequency? A study from
606 Seattle, Washington, USA. *International Journal of Retail and Distribution Management* 44(9), 903-922
607 (2016).

608 Jiao, J., Moudon, A. V., Drewnowski, A.: Grocery shopping: How individuals and built environments influence
609 choice of travel mode. *Transportation Research Record: Journal of the Transportation Research Board* 2230,
610 85-95 (2011).

611 Keisidou, E., Sarigiannidis, L., Maditinos, D.: Consumer characteristics and their effect on accepting online
612 shopping, in the context of different product types. *International Journal of Business Science and Applied*
613 *Management* 6(2), 31-51 (2011).

614 Kim, S. H., Mokhtarian, P. L.: Taste heterogeneity as an alternative form of endogeneity bias: Investigating the
615 attitude-moderated effects of built environment and socio-demographics on vehicle ownership using latent
616 class modeling. *Transportation Research Part A: Policy and Practice* 116, 130-150 (2018).

617 Li, S., Chen, L., Zhao, P.: The impact of metro services on housing prices: A case study from
618 Beijing. *Transportation* 46(4), 1291-1317 (2019).

619 Lin, T., Wang, D., Zhou, M.: Residential relocation and changes in travel behavior: What is the role of social
620 context change? *Transportation Research Part A: Policy and Practice* 111, 360-374 (2018).

621 Mao, Z., Ettema, D., Dijst, M.: Commuting trip satisfaction in Beijing: Exploring the influence of multimodal
622 behavior and modal flexibility. *Transportation Research Part A: Policy and Practice* 94, 592-603 (2016).

623 McFadden, D.: Economic choices. *American Economic Review* 91(3), 351-378 (2001).

624 McKinsey Company: How savvy, social shoppers are transforming Chinese e-commerce. Available at:
625 [https://www.mckinsey.com/industries/retail/our-insights/how-savvy-social-shoppers-are-transforming-chinese-](https://www.mckinsey.com/industries/retail/our-insights/how-savvy-social-shoppers-are-transforming-chinese-e-commerce)
626 [e-commerce](https://www.mckinsey.com/industries/retail/our-insights/how-savvy-social-shoppers-are-transforming-chinese-e-commerce) (2016). Accessed 20 January 2019.

627 Mehdizadeh, M., Mamdoohi, A., Nordfjaern, T.: Walking time to school, children's active school travel and their
628 related factors. *Journal of Transport and Health* 6, 313-326 (2017).

629 Melo, P. C., e Silva, J. D. A.: Home telework and household commuting patterns in Great Britain. *Transportation*
630 *Research Part A: Policy and Practice* 103, 1-24 (2017).

631 Mokhtarian, P. L., Salomon, I., Handy, S. L.: The impacts of ICT on leisure activities and travel: A conceptual
632 exploration. *Transportation* 33(3), 263-289 (2006).

633 Mokhtarian, P. L.: A conceptual analysis of the transportation impacts of B2C e-commerce. *Transportation* 31(3),
634 257-284 (2004).

635 Mokhtarian, P. L.: A typology of relationships between telecommunications and transportation. *Transportation*
636 *Research Part A: General* 24(3), 231-242 (1990).

637 Mokhtarian, P. L.: Telecommunications and travel: The case for complementarity. *Journal of Industrial*
638 *Ecology* 6(2), 43-57 (2002).

639 Motoaki, Y., Daziano, R. A.: A hybrid-choice latent-class model for the analysis of the effects of weather on
640 cycling demand. *Transportation Research Part A: Policy and Practice* 75, 217-230 (2015).

641 Nelson, N. M., Foley, E., O'gorman, D. J., Moyna, N. M., Woods, C. B.: Active commuting to school: How far is
642 too far? *International Journal of Behavioral Nutrition and Physical Activity* 5(1), 1 (2008).

643 Pawlak, J., Polak, J. W., Sivakumar, A.: Towards a microeconomic framework for modelling the joint choice of
644 activity-travel behaviour and ICT use. *Transportation Research Part A: Policy and Practice* 76, 92-112 (2015).

645 Piatkowski, D. P., Marshall, W. E.: Not all prospective bicyclists are created equal: The role of attitudes,
646 socio-demographics, and the built environment in bicycle commuting. *Travel Behaviour and Society* 2(3),
647 166-173 (2015).

648 Rotem-Mindali, O., Weltevreden, J. W. J.: Transport effects of e-commerce: What can be learned after years of
649 research? *Transportation* 40(5), 867-885 (2013).

650 Rushton, A. M., Carson, D. J.: The marketing of services: Managing the intangibles. *European Journal of*
651 *Marketing* 23(8), 23-44 (1989).

652 Salomon, I.: Telecommunications and travel relationships: A review. *Transportation Research Part A:*
653 *General* 20(3), 223-238 (1986).

654 Salomon, I.: Telecommunications and travel: Substitution or modified mobility? *Journal of Transport Economics*
655 *and Policy* 19(3), 219-235 (1985).

656 Scheiner, J., Holz-Rau, C.: Changes in travel mode use after residential relocation: A contribution to mobility
657 biographies. *Transportation* 40(2), 431-458 (2013).

658 Shabanpour, R., Golshani, N., Tayarani, M., Auld, J., Mohammadian, A. K.: Analysis of telecommuting behavior
659 and impacts on travel demand and the environment. *Transportation Research Part D: Transport and*
660 *Environment* 62, 563-576 (2018).

661 Shi, K., De Vos, J., Yang, Y., Witlox, F.: Does e-shopping replace shopping trips? Empirical evidence from
662 Chengdu, China. *Transportation Research Part A: Policy and Practice* 122, 21-33 (2019).

663 Shi, K., De Vos, J., Yang, Y., Witlox, F.: Does purchasing intangible services online increase the frequency of
664 travel to consume these services? Under review (2020).

665 Sim, L. L., Koi, S. M.: Singapore's Internet shoppers and their impact on traditional shopping patterns. *Journal of*
666 *Retailing and Consumer Services* 9(2), 115-124 (2002).

667 Sun, B., Ermagun, A., Dan, B.: Built environmental impacts on commuting mode choice and distance: Evidence
668 from Shanghai. *Transportation Research Part D: Transport and Environment* 52, 441-453 (2017).

669 Train, K. E.: *Discrete Choice Methods with Simulation*. Cambridge University Press (2009).

670 Wang, B., Shao, C., Li, J., Weng, J., Ji, X.: Holiday travel behavior analysis and empirical study under integrated
671 multimodal travel information service. *Transport Policy* 39, 21-36 (2015).

672 Wang, D., Law, F. Y. T.: Impacts of Information and Communication Technologies (ICT) on time use and travel
673 behavior: A structural equations analysis. *Transportation* 34(4), 513-527 (2007).

674 Weltevreden, J. W. J., Rietbergen, T. V.: E-shopping versus city centre shopping: The role of perceived city centre
675 attractiveness. *Tijdschrift voor Economische en Sociale Geografie* 98(1), 68-85 (2007).

676 Weltevreden, J. W. J., Rotem-Mindali, O.: Mobility effects of b2c and c2c e-commerce in the Netherlands: A
677 quantitative assessment. *Journal of Transport Geography* 17(2), 83-92 (2009).

678 Weltevreden, J. W. J.: Substitution or complementarity? How the Internet changes city centre shopping. *Journal of*
679 *Retailing and Consumer Services* 14(3), 192-207 (2007).

680 Xi, G., Cao, X., Zhen, F.: The impacts of same day delivery online shopping on local store shopping in Nanjing,
681 China. *Transportation Research Part A: Policy and Practice* 136, 35-47 (2020).

682 Yang, M., Li, D., Wang, W., Zhao, J., Chen, X.: Modeling gender-based differences in mode choice considering
683 time-use pattern: Analysis of bicycle, public transit, and car use in Suzhou, China. *Advances in Mechanical*
684 *Engineering*. <http://dx.doi.org/10.1155/2013/706918> (2013).

685 Young, M., Blainey, S.: Railway station choice modelling: A review of methods and evidence. *Transport*
686 *Reviews* 38(2), 232-251 (2018).

687 Zhao, P., Li, S.: Bicycle-metro integration in a growing city: The determinants of cycling as a transfer mode in
688 metro station areas in Beijing. *Transportation Research Part A: Policy and Practice* 99, 46-60 (2017).

689 Zhao, P., Zhang, Y.: Travel behaviour and life course: Examining changes in car use after residential relocation in
690 Beijing. *Journal of Transport Geography* 73, 41-53 (2018).

691 Zhen, F., Cao, X., Mokhtarian, P. L., Xi G.: Associations between online purchasing and store purchasing for four
692 types of products in Nanjing, China. *Transportation Research Record: Journal of the Transportation Research*
693 *Board* 2566, 93-101 (2016).