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The impact of online food delivery service on eating-out behavior: a case of Multi-Service Transport Platforms (MSTPs) in Indonesia

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Abstract

Online food delivery services, provided under the multi-service transport platforms such as Grab and Gojek, could significantly change people's eating-out behavior, which could also change the spatial distribution of restaurants in the long run. This study attempts to empirically identify factors affecting people's preference on the use of online food delivery services using stated preference (SP) survey data collected with a multi-day smartphone-based travel diary survey in Jakarta, Indonesia. In the survey, we randomly chose observed eating-out trips (i.e., revealed preference (RP)) from a travel diary and asked whether the respondents would like to shift to an online food delivery service in a hypothetical situation in which the delivery cost, delivery time, food cost, and available food types vary across questions. This RP–SP combination allows us to elicit respondents' preference under the real time–space constraints they had (e.g., he or she must start to work again from 13:00). Our empirical analysis confirms that delivery time and delivery cost are important factors affecting people's preference. We also discuss the long-term impact of the behavioral changes on the spatial distribution of online food merchants and its policy implications.

Keywords Multi-service transport platforms (MSTPs) · Online food delivery service · Eating-out behavior · RP–SP combination · Propensity score · Panel mixed logit

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Introduction

Information and communication technologies (ICTs) are the critical enablers of innovation in transport systems and daily lives. ICTs improve people's access to goods, services, and even jobs through virtual connectivity, allowing them to participate in activities across space and time. The ICT systems are evolving quickly and have the potential to influence people's activity and travel patterns. In the short term, ICTs have been observed to substitute, complement, and modify physical travel while improving access to activity opportunities (Salomon 1986; Mokhtarian 1990; Salomon and Mokhtarian 2007; Mokhtarian et al. 2015). Meanwhile, in the long term, they have the potential to affect congestion, emission levels, and urban form. With such important policy-level impacts, analyzing the complex interrelationships between ICT and activity–travel behavior has become an essential theme in transportation research in recent years (Varghese et al. 2021).

One of the latest ICT innovations is multi-service transport platforms (MSTPs). By utilizing the innovation of technology to improve people's daily lives, MSTPs can be defined as an online-based platform that provides access to a wide range of services, including ride-hailing transportation, food delivery service, courier service, and daily need services (such as cleaning services, massages, and hair salons). The main components of the MSTPs are (1) the efficient provision of transport services through real-time data processing and (2) the integration of transportation services and other daily life support services. MSTPs play the role of a mediator between the demand from the consumer's side and the supply from the provider's side and get involved in the direct distribution of goods and services by relying on their drivers and fleets. In daily life, the presence of MSTPs can change how people virtually access the services to fulfil their daily needs. MSTP allows people to fulfil their needs including goods (e.g., meals and groceries) and services (e.g., massage service and car repair) without traveling.

In Indonesia, MSTPs (e.g., Gojek and Grab) have become an important part of people's daily life (Irawan et al. 2019&2020). One of the most used MSTP services is the online food delivery service, where people can order foods from food merchant partners across Indonesia. MSTPs allow people to virtually access the services, relaxing their time and space constraints. Because they do not need to allocate time to travel to get their meal, they can use the time to perform other activities. Pigatto et al. (2017) found that online food delivery services allow consumers to have a more comprehensive range of options to optimize their time usage, resulting in the rapid growth of online delivery services. From the behavior study perspective, several studies found a positive relationship between attitude toward technology adoption and behavioral intention (Chang et al. 2012; Ingham et al. 2015). The rise of such online food delivery services may change eating-out behavior (demand side) and merchant behavior (supply side) as well as the interactions between consumers and food merchants (Atasoy et al. 2019). While the impacts of online food delivery services have been explored, as mentioned, more empirical works are certainly needed particularly to improve our understanding of the indirect impacts of food delivery services.

Given the presented background, this study empirically identifies the impacts of the contextual factors (i.e., time–space constraints and having a meal with friends/colleagues) as well as the service level factors (including delivery cost, delivery time, food cost, and available food types) on the use of online food delivery services using a stated preference (SP) survey data collected together with a multi-day smartphone-based travel diary survey in

Jakarta, Indonesia. We believe that controlling contextual factors is key to not mislead the impacts, which have not been well addressed in existing studies. More specifically, a longer waiting time for food would prevent people from using online food delivery services, partially because of time–space constraints they have. For example, in the case of lunchtime, people must go back to their office after getting lunch; thus, people may not be able to use the food delivery service if the waiting time is too long. In other words, ordering food from a distant place would be possible only when time–space constraints are satisfied, but this aspect has not really been explored in the literature. Another critical point that needs to be considered is that people often eat out to interact with friends and colleagues. With the consideration of this social interaction function of the meal, it seems evident that not all eating-out trips would be replaced with an online food delivery service. If the online food delivery service reduced the number of merchants in the central area of the city, as discussed previously, the social interaction function that merchants and transport systems have jointly provided (Urry 2007) would be decreased. Understanding such social impacts of online food delivery services is crucial in forming a better public policy, yet the relevant works are still very limited.

Two efforts have been made in the empirical analysis to avoid potential biases in the estimated impacts. First, contextual factors vary across trips; thus, it is not easy to set the context in the standard SP technique where all information is hypothetical (Hensher and Reyes 2000). To give a realistic context, we use a stated adaptation survey scheme: people first join an app-based activity–travel diary survey, and they are asked about the possibility of shifting to the use of online food delivery service for a particular eating-out trip. This allows for reflecting on the actual context the person had. However, it inevitably leads to another challenge, i.e., a self-selection issue: the population in the data set becomes not all individuals in the society, but all individuals who made eating-out trips, potentially leading to bias in the model estimation results. To control this potential bias, we employ one of the propensity score methods, the inverse probability weighting (IPW) method: we first estimate the propensity score model using a binary logit model (alternatives: eating-out and online food delivery service) to obtain the probability of eating out. We then use the probability to generate the weight used in the final model estimation to identify whether individuals who made eating-out trips would shift to online food delivery service under the hypothetical service level shown in the SP question. Another important point to note is that although the presented survey method would let people consider contextual factors they had, the analyst typically cannot observe all contextual factors. We employ the mixed logit model to control these unobserved contextual factors where the random term varies across eating-out trips.

The remaining sections are organized as follows. Section 2 briefly introduces the study area and the survey scheme. In Sect. 3, the model used in the empirical analysis is presented. Section 4 introduces the data used in this study. Section 5 discusses the model estimation results and other findings. Section 6 summarizes our key findings and the remaining challenges.

Study area and survey

In Indonesia, there were more than 500,000 food merchants in 2020 that partnered up with MSTPs for food distribution and more than 22 million active users every week. MSTPs'

Fig. 1 Map of study area in Jakarta, Indonesia

online food delivery service has been dominating 70–75% of Indonesia's online food delivery order market (Gojek News, 2019). Our study area is Jakarta, the capital city of Indonesia (Fig. 1). Jakarta has a very high population density of 14,464 people per square kilometer (37,460/sq mi), while the metropolitan area of Jabodetabek has a density of 4,383 people per square kilometer (11,353/sq mi). Jakarta also has the highest number of MSTP users among other cities in Indonesia, where around 8.8 million people (30–40% of the population) are active MSTP users. With regards to the online food delivery service activities, as of the year 2018, the Central Bureau of Statistics Indonesia confirms that 8.6% of food and beverages were ordered using online services (BPS-Statistics Indonesia, 2018).

To analyze the impact of MTSPs on an individual's eating behavior, we conducted a stated adaptation SP survey together with the multi-day smartphone app-based travel diary (revealed preference (RP)) survey, in Jakarta, Indonesia. Although we conducted the two-week travel diary survey from January 28th to February 10th, 2020, the SP question was generated only based on the RP data collected from January 28th to February 3rd to ask respondents to answer the questions within the survey period. We recruited respondents using social medias including Facebook, WhatsApp, and Instagram. Specifically, we first asked a screening questions to select the candidates who satisfy the following conditions: (1) 18 years old or more, (2) working in South Jakarta, Indonesia, and (3) users of online food delivery services (i.e., GoFood by Gojek and/or GrabFood by Grab). We then explained the details of survey's technical aspects, including their responsibilities and incentives (300,000 IDR = 20.8 USD) that the respondents will get after the completion of the survey. In the survey, we used a smartphone-based app called X-ING (by Mobile Market Monitor (MMM), www.mobilemarketmonitor.com). The application provided a wide range of travel attributes, including location (origin and destination), travel time, travel purpose (activity), route choice (by GPS tracking), and mode choice (see Safira et al. (2021) for the details survey design and implementation).

The initial number of participants was 312. Out of 312, 225 participants completed the two-week travel diary survey. For those who completed travel diary survey and who made eating-out trips, we further asked them to answer SP questions. The SP survey was designed and implemented to observe preferences on the respondents' eating behavior when the online food delivery service was improved. This is one type of stated adaptation question (Lee-Gosselin 1996; Danaf et al. 2019), where the experimental design is framed around an individual's current experience, and they are asked to indicate their reaction to some change in the individual decision context (See Feneri et al. (2021) for further discussions on the advantages of using a stated adaptation survey). More specifically, our survey employed both *a pivoting technique*, that is, the attributes of the alternatives are pivoted around the respondent's knowledge base (Hess and Rose 2009; Hensher et al. 2015), and a *framing technique*, that is, the situation is framed into the individual choice context to capture reactions to situational changes (Train and Wilson 2008; Feneri et al. 2021). By doing this, the real RP context, including the time–space constraints the respondents had, was reflected when answering the question.

This survey was designed particularly to capture changes in eating-out behavior. Hypothetical scenarios with regard to online food delivery options were provided to users, and their choice of whether they will shift to online food delivery or continue to conduct the eating-out activity was observed. This is an important aspect with respect to understanding the effects of ICT on travel behavior as it will aid in analyzing if ICT will substitute physical travel in the case of eating-out trips. For each user, one of their eating-out activities was selected at random from the first week of their travel, and then based on their RP, attribute levels in SP were decided. Each user was then provided with five choice scenarios to choose between the online food delivery option and their present eating-out trip. This stated adaptation survey is deemed better than when all choice contexts in an SP survey are purely hypothetical. It is because such a design accounts for context-dependent factors such as motivation and constraints they had at that time. In addition, this kind of stated adaptation survey design could capture the complex interdependencies between ICT use and travel because their travel decisions may come from extrinsic motivations (e.g., getting a lunch meal) or intrinsic motivations (e.g., interacting with friends, traveling, and having lunch).

The attribute levels for the SP survey were generated using the RP information as shown in Table 1. For (a) delivery time for online food delivery, the travel time information captured from travel before the eating-out activity (for one randomly selected context) was utilized to create five different levels. Meanwhile, for (b) delivery cost, travel distance information for the previous trip before the eating-out activity was first captured automatically through GPS sensors in the smart phone, and then multiplied with an assumed per km cost for delivery of 6,000 IDR (0.42 USD) across five different levels. For (c) a combination of ordered food types, the same categories offered to users for their eating-out trips were utilized to create four different levels, denoting the combination and the number of food items ordered. Finally, (d) food cost for online food delivery and information from RP on the user's actual expenditure on the eating-out activity was utilized to create five different levels. The variations in the food cost are an important factor, as often it is seen that MSTPs collaborate with food merchants to provide services at discounted rates.

The five scenarios were presented to participants with two choices in each, with the actual eating-out trip information on the left side and the attribute levels for the online food delivery option on the right (Fig. 2), where alternatives are (1) continuing to make the eating-out trip, and (2) shifting to the online food delivery services. As the SP survey was conducted later, we strived to make respondents remember the actual conditions at the time of participating in that activity. By showing the date when they took the eating-out trip, it is hoped that the respondents will be able to remember the conditions and constraints they had at that time. The following question was then posed to the respondents as part of the SP survey, "*by considering all the activities and constraints you have at that time if the follow-*

Table 1 Attributes and levels for stated adaptation survey for eating-out activities

Attributes	Level
a) Delivery time for online food delivery. *(based on the actual travel time from the travel diary data; revealed-preference-based question)*	1. 0.4* actual travel time 2. 0.7*actual travel time 3. 1.0*actual travel time 4. 1.3*actual travel time 5. 1.6*actual travel time
b) Delivery cost for online food delivery. *(based on the actual travel distance from the travel diary data; revealed-preference-based question)*	1. 0.4*6,000 IDR*actual travel distance 2. 0.7*6,000 IDR*actual travel distance 3. 1.0*6,000 IDR*actual travel distance 4. 1.3*6,000 IDR*actual travel distance 5. 1.6*6,000 IDR*actual travel distance
c) Combinations of online food delivery's food types (1. Beverages, 2. Snacks/Sweets, 3. Fast food, 4. Indonesian food, 5. Western food, 6. Eastern food, 7. Bakso/Noodles)	1. One food type 2. Three food types 3. Five food types 4. Seven food types
d) Food cost for online food delivery. (based on the actual food cost from the activity information data; *revealed-preference-based question*)	1. 0.8*actual food cost 2. 0.9*actual food cost 3. 1.0*actual food cost 4. 1.1*actual food cost 5. 1.2*actual food cost

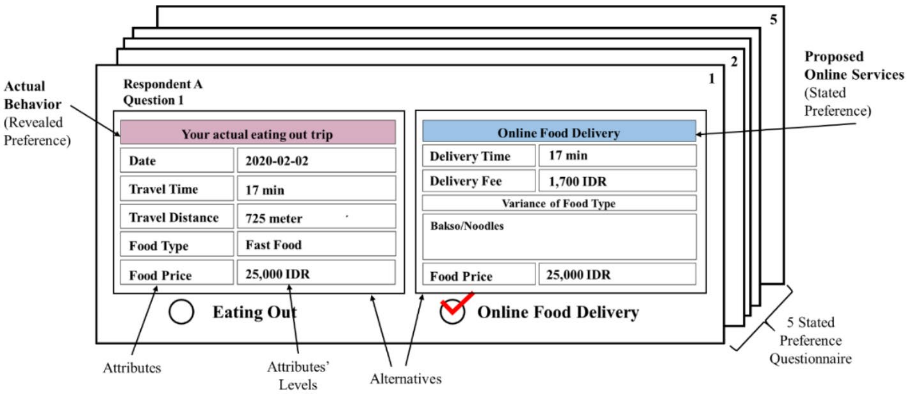


Fig. 2 Stated adaptation survey questionnaire for eating-out behavior

ing online food delivery service is available, will you be shifting from eating out to ordering from an online food delivery service?"

Modeling framework

This section introduces a modeling framework to empirically identify the impacts of the level of service factors and contextual factors on the use of online food delivery services. As we briefly discussed in Sect. 1, it is not easy to introduce all contextual factors in a standard SP survey where all choice contexts are purely hypothetical. A feasible way to introduce realistic contexts is to ask respondents to answer SP questions in a real RP context (Huynh et al. 2017). We employed this stated adaptation survey approach. Specifically, we randomly picked up observed eating-out trips and asked respondents to answer whether they would like to shift to online food delivery services given the RP context. However, this process would lead to a self-selection issue by excluding respondents who did not have eating-out trips. To alleviate this self-selection issue, we used an IPW method. In the method, we first estimated the propensity of having an eating-out trip for each eating behavior where the alternatives of eating behavior include eating-out and online food delivery service. Using the weights constructed from the estimated propensities, we developed an SP model on the use of online food delivery services. This process could remove the biases caused by the fact that the sample (i.e., people who made eating-out trips) used for the model estimation is systematically different from the population (i.e., people who made eating-out trips and who had a meal using an online food delivery service).

Note that because online food delivery services are already available in the market, it apparently seems that the RP data are good enough to explore preferences on the use of online food delivery service, but taking the proposed SP approach is crucial to properly reflect contextual factors. It is well known that contextual factors are dominant in decision making; however, many of them are typically unobserved (Chikaraishi et al. 2009, 2011). To control these unobserved contextual factors, it would be straightforward to show different online food delivery services to respondents repeatedly under the same RP context and observe how respondents change their decisions. Such repeated observations allow for introducing additional random terms representing unobserved trip-specific contextual factors analogous to random effects in panel data analysis. In the empirical analysis of this study, we employed a panel mixed logit model to control such unobserved trip-specific contextual factors. It should also be noted that a popular SP–RP combined model (Ben-Akiva and Morikawa 1990) typically allows us to obtain statistically accurate estimation based on actual and hypothetical behavior (Sanko 2001), but a straightforward application of this approach is not appropriate for our case study because, different from Ben-Akiva and Morikawa (1990), the SP data were not obtained from the population. In Sect. 3.1, we briefly introduce the model to estimate the propensity score. Section 3.2 introduces a panel mixed logit model on the use of online food delivery services.

Estimation of the Propensity score

We assumed that whenever people want to use food services, they have two options: going to restaurants (i.e., making eating-out trips) and using online food delivery services. Given this assumption, we obtained the propensity of having an eating-out trip by estimating the following logit model as:

$$p_{it} = \frac{\exp\left(v_{it}\right)}{\exp\left(v_{it}\right) + 1} \tag{1}$$

where p_{it} is the probability of choosing eating-out in the t-th eating behavior of individual i (called propensity score), $t \in T = \{T_e, T_{fd}\}$, where T is a set of all observed eating behavior, T_e is a set of observed eating-out trips, and T_{fd} is a set of observed online food delivery service uses; v_{it} is the systematic utility for making an eating-out trip, and $v_{it} = \beta \mathrm{x_{it}}$, where $\mathrm{x_{it}}$ is a vector of explanatory variables, and β is a vector of parameters to be estimated. After obtaining the estimated propensity score $\hat{p}_{it}$, we took the inverse of propensity score as a weight, i.e., $\hat{w}_{it} = 1/\hat{p}_{it}$.

Model specification for eating choice behavior

We then developed a panel binary mixed logit to model whether individuals who made eating-out trips would adapt to the online food delivery service shown in the SP question. The utility is defined as:

$$u_{sit} = \alpha \mathrm{z_{sit}} + \eta_{it} + \varepsilon_{sit} \tag{2}$$

where α is a vector of parameters to be estimated, $\mathrm{z_{sit}}$ is a vector of explanatory variables for the s-th SP question for individual i's t-th trip ($t \in T_e$), and ϵ_{sit} is the error term following a standard Gumbel distribution. η_{it} is another random term following a normal distribution. This would capture the impacts of unobserved trip-specific attributes on the choice. The probability of shifting to an online food delivery from eating-out trip is defined as follows.

$$p_{sit} = \frac{\exp(\alpha \mathrm{z_{sit}} + \eta_{it})}{\exp(\alpha \mathrm{z_{sit}} + \eta_{it}) + 1} \tag{3}$$

The following weighted likelihood function LL was used in the model estimation to control possible biases caused by the self-selection issue mentioned.

$$LL = \int \sum_i \sum_{t \in t_e} \hat{w}_{it} \ln(p_{sit})\, \varphi(\eta_{it}) d\eta_{it} \tag{4}$$

For the model estimation, we used the *glmer* function of R-package lme4 (Bates and Sarkar 2007)

Data

In this study, we collected data from the respondents who completed the multi-day activity–travel diary survey. We found that 114 respondents were conducting eating activities that included both eating-out trips and ordering foods through online delivery services. Out of 557 eating activities, 272 were eating-out trips, and the remaining 285 were the use of online food delivery services. We also captured personal socioeconomic and demographic characteristics from users. It included questions on gender, age, income, family size, vehicle ownership, education level, and occupation type.

Table 2 summarizes the number of individuals, samples of SP questionnaire, number of eating activities, and the explanatory variables used for the model estimation and their basic statistics. For the individual and household attributes, we used gender, age, marital status, respondents' occupation type, average monthly individual income, average monthly household expenses, dummy variables indicating the location before and after eating behavior, and the desire to interact with others. The desire to interact with others was constructed from a 1–6 Likert scale attitudinal question, that is, "If I have someone to eat out with, I prefer to eat in a real restaurant rather than using online-based food delivery services," where negative answers (strongly disagree, disagree, and slightly disagree) are set as zero, while positive answers (slightly agree, agree, and strongly agree) are set as one.

For the eating choice behavior model estimation, we also used the variables from the SP questionnaire as our explanatory variables. Table 3 describes the variables from the SP questionnaire that represented the online food delivery services, including the variety of food, delivery time (in minutes), delivery cost (in IDR), and food cost (in IDR).

Results

To handle the self-selection issue, we first estimated the propensity score model. Table 4 shows the estimation results for the model which predicts the probability that an individual will eat out. The results confirm that people who are young, male, or married or have high-income tend to choose eating out rather than online food delivery services. Regarding the scheduling-related factors, it is confirmed that those who are office worker, where most of them have a job with a fixed schedule, tend to choose eating out, and people who were staying at the workplace tend to choose eating out as well. We also found that those who have a desire to interact with others while eating tend to choose eating out rather than online food delivery services.

Based on the estimation results shown in Table 4, we calculated the weights used in the following model estimations. Table 5 shows the estimation results of the models for eating choice behavior (i.e., whether individuals who made eating-out trips shift to an online food delivery service shown in SP question). We estimated how the presence of MSTP's online food delivery service will affect people's eating behavior by including the variables such as desire to interact with others, delivery time (in an hour), delivery cost (in 100,000 IDR), variety of food, food cost (in 100,000 IDR), the actual travel time for an eating-out trip, and the actual travel cost for the eating-out trip (in 100,000 IDR). In total, we estimated four models to identify the impacts of adding a random term representing unobserved trip-specific contextual factors and the impacts of the weights introduced. The results confirm the significant impacts of both the random term and weights on the estimated parameters. More specifically, the introduction of the random term changes the sign of parameter on delivery time, while taking weights into account changes the statistical significance of delivery time. The latter indicates that the population would be more sensitive to delivery time than the sample (i.e., eating-out trips). This can be logically understood because making eating-out trips implies that people have less time constraints compared with those who used online food delivery services. The estimated parameter values of the model with weights and ran-

Table 2 Data description of variables

Variable	Category	Total	Percentage
Eating behavior (RP)		557	100.00%
	Eating-out activities	272	48.83%
	Online food delivery services	285	51.17%
Eating behavior (SP)		570	100.00%
	Keep making an eating-out trip	271	47.54%
	Shifting to order online food delivery service	299	52.46%
Explanatory Variables			
Gender	Male	49	42.98%
	Female	65	57.02%
Age (years)	18–22	12	10.53%
	23–27	44	38.60%
	28–32	28	24.56%
	33–37	18	15.79%
	38–42	12	10.53%
Marital status	Single	72	63.16%
	Married	42	36.84%
Job	Office worker	107	93.86%
	Non-office worker	7	6.14%
Average individual income per month (in mil. IDR)	Less than 1	3	2.63%
	1–1.99	7	6.14%
	2–3.99	21	18.42%
	4–5.99	42	36.84%
	6–7.99	15	13.16%
	8–9.99	10	8.77%
	More than 10	16	14.04%
Average household expenses per month (in mil. IDR)	Less than 1	4	3.51%
	1–1.99	7	6.14%
	2–3.99	24	21.05%
	4–5.99	42	36.84%
	6–7.99	13	11.40%
	8–9.99	8	7.02%
	More than 10	16	14.04%
Location Attributes of Activities			
Home before	Location of previous activity is home	55	9.65%
	Otherwise	515	90.35%
Home after	Location of next activity is home	65	11.40%
	Otherwise	505	88.60%
Work before	Location of previous activity is workplace	150	26.32%
	Otherwise	420	73.68%
Work after	Location of next activity is workplace	110	19.30%
	Otherwise	460	80.70%
Desire to interact with others	Having a desire to interact with others	390	68.42%
	Otherwise	180	31.58%

dom effects indicate that the delivery time, delivery cost, the actual travel time, and the actual travel cost are significant, while the variety of foods, food cost, and desire to interact with others are not significant.

Table 3 Stated preference survey variable

Variable	Category	Total	Percentage
Sample size		570	100.00%
Variety of foods	1	145	25.44%
	3	133	23.33%
	5	142	24.91%
	7	150	26.32%
Delivery time (in minutes)	< 10	248	43.51%
	10–19	165	28.95%
	20–29	57	10.00%
	30–39	31	5.44%
	40–49	17	2.98%
	50–59	20	3.51%
	≥60	32	5.61%
Delivery cost (in IDR; 10,000 IDR = 0.69 USD)	< 10,000	242	42.46%
	10,000–29,999	158	27.72%
	30,000–49,999	68	11.93%
	50,000–69,999	40	7.02%
	70,000–89,999	14	2.46%
	≥90,000	48	8.42%
Food cost (in IDR; 25,000 IDR = 1.74 USD)	< 25,000	148	25.96%
	25,000–74,999	240	42.11%
	75,000–124,999	75	13.16%
	125,000–174,999	28	4.91%
	≥175,000	79	13.86%

Based on our findings, we calculated the value of travel time for an eating-out trip and the value of waiting time for an online food delivery service. Note that the absolute values of parameters for SP variables are higher than those for RP variables as indicated by Ben-Akiva and Morikawa (1990), and thus the absolute values between RP and SP should not be directly compared. To make the comparison possible, we calculated the value of travel time for an eating-out trip and the value of waiting time for online food delivery services, where the former is 54,837 IDR/hour while the latter is 62,148 IDR/hour. This is apparently counterintuitive because people can conduct other activities while waiting for online food delivery services, and thus the value of waiting time should be lower than the value of travel time. However, several potential reasons make the value of waiting time greater than the value of travel time. First, using an online food delivery service is less flexible in terms of schedule modifications. For example, when travel time/food delivery time is increasing because of traffic congestion against their expectations, those who choose to eat out can change their destination to obtain their meal within the time constraint, but those who choose food delivery service may not be able to do that. Another possible reason is that a longer delivery time implies that people may not be able to have a fresh-cooked dish. Although we should further confirm whether these reasons are true in the future, our empirical results indicate that the impacts of online food delivery services on the spatial distribution of online food merchant's world could be modest because most people may use online food delivery services nearby, and thus merchants moving out to suburbs may have fewer online food delivery services' customers. However, it should be noted that in eating-out trips, they must make an additional trip to return to the original location, and thus the

Table 4 The estimation results of the propensity score model

Explanatory Variables	Estimate	t-Values	Sig. Sign
Constant	–0.71	–1.08	
Age	–0.07	–5.14	**
Gender (0: male; 1: female)	–0.21	–2.21	*
Marital status (0: single; 1: married)	0.54	3.03	**
Average individual monthly income (mil IDR)	0.05	2.25	**
Average household monthly expenses (mil. IDR)	0.03	2.11	*
Office worker (0: non-office worker; 1: office worker)	2.04	5.03	**
Dummy for home before (1: location of the previous activity is home; 0: otherwise)	0.21	1.06	
Dummy for home after (1: location of next activity is home; 0: otherwise)	0.04	0.21	
Dummy for workplace before (1: location of the previous activity is workplace; 0: otherwise)	0.61	3.08	**
Dummy for workplace after (1: location of next activity is a workplace; 0: otherwise)	–0.01	–0.06	
Desire to interact with others (1: having a desire to interact with others; 0: otherwise)	0.32	3.87	**
Akaike Information Criterion (AIC)	284.10		
Initial log-likelihood	–386.08		
Final log-likelihood	–294.95		
Sample size	557		

** significant at 1% level; * significant at 5% level

benefits of using online food delivery service would still be high even when the value of waiting time is higher than the value of travel time.

As confirmed, delivery time is one of the main factors affecting the use of online food delivery services. It may be natural to consider that delivery time will be decreased with the increased number of merchants nearby, since it makes it easier to find MSTP drivers. To confirm this hypothesis empirically, we further explored the association between delivery time and the density of online food merchants. We first prepared travel time and delivery time data of online motorbike ride-hailing service (online *ojek*) using Google MAPs route search service for origin-destination (OD) pairs of 262 zones in Jakarta (Fig. 3). More specifically, we collected travel time and travel cost data of online *ojek* on Monday, November 2nd, 2020, at 10:00 a.m. Note that the selection of time would inevitably affect the results, since travel time and cost would be dynamically adjusted depending on the balance between demand and supply. We found that the demand has three peak hours: 8:00–9:00, 12:00–13:00, and 18:00–20:00, which would correspond to breakfast, lunch, and dinner (Safira et al. 2021), but we could not obtain the supply information. While noting that the current study focuses on off-peak hours, we should further investigate both the demand and supply to further understand the dynamics of travel time and cost of online *ojek*. In Indonesia's Google MAPs route search service, there is information on the online ride-hailing service's approximation cost for motorbike and car ride-hailing services. We took the average cost

Table 5 The model estimation results of eating choice behavior

	Without η_{it}						With η_{it}					
	Without Weight			**With Weight**			**Without Weight**			**With Weight**		
	Estimate	**t-values**		**Estimate**	**t-values**		**Estimate**	**t-values**		**Estimate**	**t-values**	
Constant	–2.34	–13.12	**	–2.37	–14.00	**	–0.53	–0.41		–0.21	–0.15	
Desire to interact with others	–0.21	–1.35		–0.28	–1.40		–0.14	–0.69		–0.37	–1.51	
Delivery time (hour)	–0.33	–2.45	*	0.76	1.68		–1.14	–2.13	*	–1.15	–2.14	*
Delivery cost (100,000 IDR)	–0.03	–3.51	**	–1.81	–2.92	**	–0.81	–1.36		–0.63	–3.97	**
Variety of foods	0.41	12.63	**	0.46	11.40	**	–0.003	–0.08		–0.01	0.13	
Food cost (100,000 IDR)	0.52	4.76	**	0.49	3.25	**	–0.12	–0.74		–0.15	–1.00	
Travel time (hour)	–0.14	–2.29	*	–0.84	–1.0438		–0.146	–1.93		–0.25	–1.74	
Travel cost (100,000 IDR)	–0.07	–1.35		–0.43	–0.82		–0.062	–0.07		–0.15	–1.88	
Random effect: σ_{η}^{2}							9.737			9.915		
AIC	422.54			437.88			361.43			246.74		
Initial log-likelihood	–395.09			–395.09			–395.09			–395.09		
Final log-likelihood	–252.98			–240.48			–221.40			–215.54		
Sample size	570											

** significant at 1% level; * significant at 5% level; (.) significant at 10% level

At the time of the survey was conducted 1 USD = 14,602.75 IDR

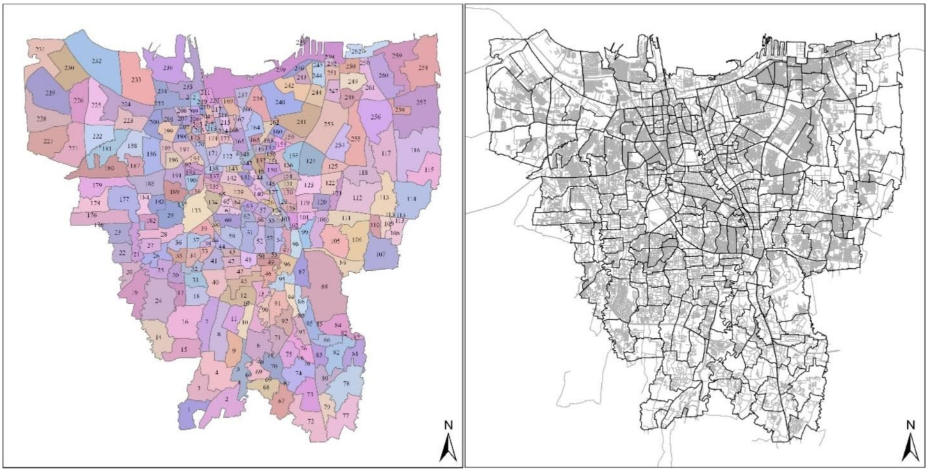


Fig. 3 Maps of 262 zones and the road networks of Jakarta

of the services as the travel cost of online motorbike ride-hailing (online *ojek*). It is noted that to order the services, people cannot use the Google MAPs directly; they must use the MSTP's application to order the services, and thus actual cost could be different from the one shown in Google MAPs. We also obtained information on delivery time and delivery cost of MSTP's online food delivery services. We used the Gojek application to obtain the information of GoFood (online food delivery services) delivery time and delivery cost from one zone to the other zones. It is noted that if we order the food using MSTP's online food delivery services, they might have some monetary incentives (e.g., coupons, price discounts, and other promotions) that may result in a different price at the time of ordering the food. However, we only included the regular average price of MSTP's online food delivery cost.

We also obtained the location information of online food merchants from Google MAPs using web crawler tools. We extracted the location information on December 3rd, 2020. The extracted data include the name of facilities/stores, type of facilities, street address, coordinate location, opening hours, and other variables. In this study, we categorized the food merchants into two groups: (1) the "combination" food merchants who provide both dine-in and online food delivery services and (2) the online food merchants who only provide an online food delivery service (no dine-in service available at their store). Regardless of the type of food merchants, we only considered the food merchants with the fixed location of stores. The mobile food merchants such as mobile street food vendors were omitted. Using the web crawler data collection method, we successfully obtained 4,458 combination food merchants and 3,718 online food merchants across the area in Jakarta (Fig. 4).

The delivery time includes both travel time by online *ojek* and the additional time such as time for searching a driver. Because this additional time makes online foo1-d delivery service less efficient, we employed the ratio of delivery time and travel time by online *ojek* as a service efficiency index for online food delivery service. Figure 5 shows the indicator values by the density of food merchants. The figure indicates that the additional time decreases with an increased density of online food merchants. In other words, people have more time-saving benefits if they order foods from an area that has a high density of online food merchants.

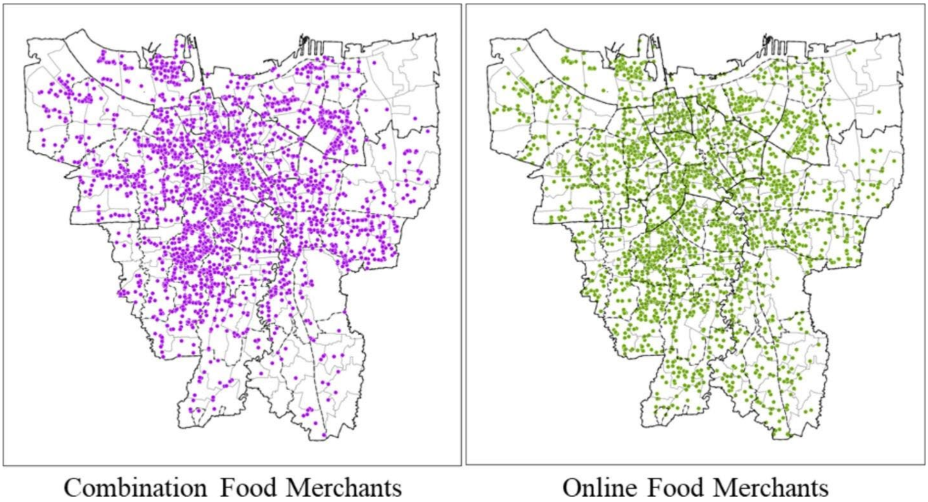
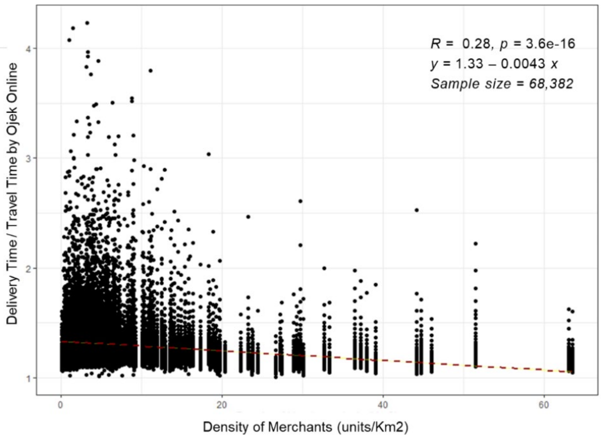


Fig. 4 Distribution of food merchants

Fig. 5 Correlation between service efficiency index and the density of combination and online food merchants



In general, drivers standby around areas that have higher demand. If the drivers standby in areas that have more online food merchants, the chance for them to obtain some orders is higher than in areas with a smaller number of online food merchants. Having more drivers in the area may reduce the additional time for searching for a driver and hence reduce the delivery time. This new kind of agglomeration must be considered when we explore the long-term impacts of online food delivery services on the distribution of food merchants. From the modeling perspective, in the future, delivery time should be dealt with as an endogenous variable because delivery time depends on the demand in the area.

Discussion and conclusions

This study examined the impact of online food delivery services on individuals' eating activity behavior. The empirical analysis was conducted using stated adaptation survey data collected in Jakarta, Indonesia, together with multi-day smartphone-based travel diary survey data. Although this stated adaptation survey leads to a self-selection issue in the sense that all the respondents were persons who made eating-out trips, it allows us to elicit respondents' preference on the use of online food delivery services under the real time–space constraints they had. In our empirical model estimation, we used the IPWT method to control biases caused by the self-selection and introduced a random term to control unobserved trip-specific contextual factors. The empirical results indicate the importance of using both IPWT and random-effect models to alleviate the biases in the estimates.

Empirical results showed that delivery time and delivery cost, along with the other unobserved random variables, are key factors affecting people's preferences on the use of MSTPs' online food delivery services. Our empirical results also confirmed that the value of waiting time for online food delivery services (62,148 IDR/hour) is larger than the value of travel time for an eating-out trip (54,837 IDR/hour), potentially because (1) using online food delivery service is less flexible in terms of schedule modifications, and/or (2) longer delivery time implies that people may not be able to have a fresh-cooked dish, though further analysis is needed to reach a general conclusion.

The delivery time of MSTPs' online food delivery service includes both travel time by the online ojek and the additional time of searching for a driver who can pick up the order. We empirically confirmed that the additional time could be substantially shorter with the increase in the number of online food merchants nearby because drivers would standby around the area that has higher demand. This may become a new agglomeration force for online food merchants that may need to be considered when evaluating the long-term impacts of online food delivery services on urban form.

The above-mentioned findings provide several important policy implications. First, the service level of MSTPs tends to be better in central areas where well-developed public transit service is operated. It has been known that public transit development would foster the spatial agglomeration (Chatman and Noland 2011), and our findings indicate that the introduction of MSTPs would further encourage the agglomeration. Related to this, Irawan et al. (2019) empirically show that motorcycle-based ride-sourcing would work as a complementary mode for public transit. In summary, the introduction of MSTPs, together with public transit development, would enable the growth and densification of cities. Though, the adverse effects of the introduction of MSTPs such as traffic congestion need to be further explored to give a general conclusion. Another important point is that the connection to the concept of Mobility as a Service (MaaS). Recently, several studies on MaaS have been conducted, including studies exploring the users' preferences (e.g., Caiati et al. 2020) and studies exploring a better ecosystem of MaaS (e.g., Wong et al. 2020; Polydoropoulou et al. 2020), but most of them focuses on passenger transport, and less attention has been paid to the good transport including online food delivery services. Since suppliers (drivers) for both passenger and goods transport are pooled into a single platform of MSTP, our conceptual and methodological framework should also consider both passenger and goods transport together, rather than employing a traditional, vertically segmented research framework.

There are several major remaining tasks. First, we need to evaluate how merchants (as the supply side of MSTPs) react to the changes in users' behavior. Second, the use of online food delivery services should properly be embedded into an activity-based model. Although the impacts on land use may be marginal as indicated by our empirical results, travel patterns are affected by the shift from eating out to the use of online food delivery services. Another major challenge is the comprehensive evaluation of ICT tools on activity–travel behavior. Now ICT tools have tremendous impacts on our activity–travel behavior in multiple ways, including online shopping and teleworking, and having a better understanding of the negative/positive, and direct/indirect impacts of shifting to these virtual activities needs to be further explored for better policy decisions.

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Author contributions Maya Safira and Makoto Chikaraishi conceived of the presented idea, designed and implemented the data collection. Maya Safira performed the analysis. All authors discussed the results and contributed to the final manuscript.

A conflict of interest statement On behalf of all authors, the corresponding author states that there is no conflict of interest.

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