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Free-floating carsharing users’ willingness-to-pay/accept for logistics management mechanisms

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ABSTRACT

The spatio-temporal flexibility of free-floating carsharing (FFCS) fleets leads to vehicle stock imbalances across the network. One set of strategies for managing fleet distribution involves incentivising users to participate in relocating the vehicles. The objective of this study is to establish FFCS customers’ preferences for each of four incentivisation mechanisms: 1) vehicle delivery, 2) paid relocation, and 3–4) incentivisation for alternate vehicle pick-up and drop-off locations. Survey data (n = 311; collected Sept. 2017) from FFCS users in Vancouver and Washington D.C. are employed to quantify willingness-to-pay/accept (WTP/WTA) for these mechanisms. We find that a majority of respondents report positive attitudes (“definitely” or “possibly” willing to use) toward each of the four incentivisation mechanisms, with alternate drop-off the highest (57%) and paid relocation the lowest (40%). Regression analysis finds that user experiences using FFCS are generally stronger predictors of WTP/WTA than socio-demographic features, with (intuitively) the frequency of FFCS unavailability the strongest predictor. Age is the strongest socio-demographic predictor, with the WTP for vehicle delivery increasing and the size of required incentives for alternate pick-up/drop-off locations decreasing with age. Finally, we performed k-means cluster analysis of respondents based on the times-of-week that they report experiencing difficulty finding an available FFCS vehicle, and identified four distinct segments of users. However, we found generally weak relationships between WTP/WTA and the specific time-of-week periods that unavailability is experienced.

1. Introduction

Carsharing is a short-term car rental service which provides users with short-term and occasional access to the vehicles. Three common types of carsharing (round-trip, one-way station-based, and one-way free-floating carsharing [FFCS]) vary in their requirements regarding the pick-up and drop-off location of the carsharing vehicle. The one-way carsharing forms do not require users to pick-up and drop-off vehicles at the same location, whereas the round-trip model generally does (Ferrero et al., 2017; Jorge and Correia, 2013; Shaheen et al., 2016).

Studies on carsharing have incorporated various aspects, including the adoption and the characteristics of early adopters (Efthymiou et al., 2013; Efthymiou and Antoniou, 2016; Namazu et al., 2018), factors that influence usage of the service (Becker et al., 2017; Heilig et al., 2017; Zoepf and Keith, 2016), the impact of carsharing on travel behaviour, emissions, car ownership, and pre-existing modes of transport (Le Vine and Polak, 2019; Martin and Shaheen, 2011a,b), and optimal design/management of carsharing systems (Nourinejad and Roorda, 2014; Jorge et al., 2015; Schmöller et al., 2015; Deng and Cardin, 2018).

Managing the fleet logistics of carsharing systems is one of the most widely studied topics relating to free-floating systems, because of the spatio-temporal imbalance inherent to one-way operation (Cepolina and Farina, 2012; Jorge and Correia, 2013; Nourinejad et al., 2015). Two general approaches available to operators of free-floating shared mobility networks are to either 1) hire staff to rebalance the fleet distribution, or to 2) employ crowdsourcing principles to engage their

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customer base (or other casual staff) in this task. The second of these concepts, typically referred to as user-based relocation, is the focus of increasing interest (Barth et al., 2004; Jorge et al., 2015). In this study, we investigate four user-based relocation incentivisation mechanisms:

- **Vehicle delivery**: The user pays an extra fee for the operator to deliver the shared vehicle to the user, which would require the operator to either hire dedicated staff or otherwise incentivise some users to deliver the vehicles;
- **Alternate pick-up location**: The user changes their intended vehicle pick-up location and receives some discount from the operator, which requires the operator to know which zones are/will be undersupplied by shared vehicles and to implement algorithms to compute the incentive that is predicted to encourage users to change their pick-up locations;
- **Alternate drop-off location**: The user changes their intended vehicle drop-off location and receives some discount from the operator, which requires that the operator have similar knowledge and capabilities as the alternate pick-up location mechanism immediately above;
- **Paid relocation**: The user helps the operator relocate a certain number of vehicles and receives some discount. This will require the operator knows the current/future vehicle supply/customer demand distribution and computes how many vehicles to relocate and how much they should pay the users that helps in the relocation (See Brendel and Keufner (2017) as an example).

Table 1 presents examples of operators of shared-mobility fleets (both carsharing and bikesharing) that employ various of these mechanisms for fleet re-balancing.

The motivation for this study is to identify and quantify factors associated with users’ willingness-to-pay/accept (WTP/WTA) for these four incentivisation mechanisms. To query this behaviour, a web-administered survey of n = 311 existing FFCS users was undertaken in Vancouver and Washington D.C. during September 2017. The remainder of this paper is structured as follows: Section 2 reviews the existing research in management of carsharing fleet logistics, with focus on user-based relocation techniques and user response to various relocation approaches. Section 3 introduces the survey and a descriptive summary of the data. Section 4 presents results and discussion, with Section 5 summarizing and concluding the paper.

**2. Literature review**

Operator-based vehicle rebalancing (using paid staff) is the most extensively studied relocation technique within FFCS networks (Fan and David, 2013; Kek et al., 2009; Nair and Miller-Hooks, 2011). These studies typically formulate the vehicle relocation problem as integer programming, and then develop algorithms for efficient computation for large-scale systems.

Fewer studies address user-based relocation, however this strategy is the focus of increasing attention. Incentivising users to change the intended pick-up or drop-off location is the most common mechanism, as studied by Jorge et al. (2015), Di Febbraro et al. (2019) and Xu et al. (2018). Other user-based relocation techniques include trip-joining and trip-splitting. In the ‘trip-joining’ approach the operator requests that users with similar trip origins and destinations share (or ‘join’) journeys when fleet has low availability, and in the ‘trip-splitting’ approach the operator requests that users in a single travelling party take separate vehicles to a common destination (rather than travel together; see Barth et al. (2004), Herrmann et al. (2014) and Wen et al. (2017)). Other mechanisms studied in the literature are “paid relocation” (in which users are requested to make a new journey that they otherwise would not make, to relocate a vehicle; see Herrmann et al. (2014)), and operator-user collaborated carpooling (the relocation staff member give a lift to the users when moving the vehicle, see Bruglieri et al. (2018)). A limitation of these studies is the lack of quantification of carsharing users’ preferences for the various incentivisation mechanisms.

Table 2 summarises earlier studies employing survey data to establish user preferences for relocation mechanisms. In general, prior studies find that a majority of carsharing users would participate in the user-based relocation mechanisms, with the probability of participation relating positively with the size of incentive and negatively with the amount of additional walking time. However, prior studies include limited investigation of the relative importance of explanatory factors and considered a narrower range of relocation mechanisms than the present study. Therefore, this study aims to contribute to this body of literature by quantifying the influence of socio-demographic and user-experience factors on FFCS users’ willingness to participate in relocation mechanisms.

**3. Data and descriptive analysis**

Data for this study were generated in mid-September 2017 via a web-administered survey of FFCS users in Vancouver and Washington D.C (a summary of the state of the carsharing marketplaces in both cities is in Table 3). Approximately 5,500 FFCS users were invited, with 311 completing the survey (for a full-completion response rate of 6%). Respondents received incentives in the form of points that can be pooled and later redeemed in the form of gift cards. The equivalent value of the points is less than $1 per respondent. The topics covered in the survey were:

- Socio-demographics
- Current memberships of FFCS and other forms of shared mobility,
- Frequency of FFCS usage,
- Satisfaction with the current FFCS service, and
- Attitudes and willingness-to-pay/accept for the four user-based relocation mechanisms. Three types of responses were elicited for each mechanism:

1. General willingness to participate (Likert scale),
2. Willingness to participate at a prompted price point (Likert scale), and
3. Open-ended WTP/WTA (in units of currency, per minute discount or percentage discount. These are the variables we employ as dependent variables in the regression analysis in Section 4.3).

Table 4 summarises the sample and responses to the main survey questions. The distribution of respondents’ WTP/WTA attitudes/values are summarised in Table 4 (Likert scale questions and open-ended
| Type                                      | Number of respondents and year of survey | Vehicle relocation mechanism | Survey contents                                                                 | Key findings                                                                                                                                                                                                 |
|------------------------------------------|-----------------------------------------|------------------------------|---------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Shaheen et al. (2018)                    | FFCS n = 473 (Sep. 2014-Mar. 2016, San Diego) | Alternate pick-up/drop-off location | Respondents’ awareness of the user-based relocation program Frequency and willingness to participate; Reason for participating; Satisfaction with the incentive program; Intended incentive; Free driving credit vs cash | 1. A large proportion of respondents who had not take advantage of the incentive program is because their final destination was rarely within the incentive zone; 2. The alternate drop-off location incentive program is more preferred than the alternate pick-up location in this study; 3. The willingness to accept the incentive programs increases with the level of incentives; 4. Minutes were more effective than monetary incentives |
| Herrmann et al. (2014)                   | FFCS n = 87 (year of survey not stated; published 2014) | Alternate pick-up/drop-off location | Maximum walking distance; Willingness to accept a more distance car for a 1/3 price discount; Willingness to indicate destination at the beginning of the trip | 1. 80% of the users do not accept walking distance of more than 500 m, and more than 55% users do not accept waiting for a vehicle for more than 15 min (99% do not accept longer than 30 min waiting); 2. 85% of the users are willing to book a more distant car for 10 cent/km price reduction (1 one third discount). Another 13% expect a more significant discount; 3. 61% respondents prefer price discount and 31% prefer free driving minutes |
| Brendel et al. (2016)                    | One-way station-based carsharing         | Alternate drop-off location     | A function describing the relationship between incentive and additional walking time | Incentive as a function of additional walking time                                                                                                                                                     |
| Singh et al. (2015)                      | Station-based bike sharing               | Alternate pick-up/drop-off location | Maximum additional walking distance; Users’ cost on the additional walking distance | The distribution of acceptance with maximum acceptable walking distance and the amount of incentive                                                                                                    |
| Present study                            | FFCS n = 311 (Sep. 2017, Vancouver and Washington D.C.) | Vehicle delivery; Alternate pick-up/drop-off location | Willingness to pay/accept                                                      | See Section 4                                                                                                                                                                                          |
questions, and open-ended questions are bolded) and Fig. 1 (open-ended questions). The distributions in Fig. 1 show relatively small numbers of ‘non-traders’ among respondents (i.e. respondents reporting zero WTP and/or stating that they would require a 100% discount). We observe 23 non-traders for vehicle delivery (7.9%), 18 for alternate-pick-up location (6.2%), 17 for alternate-drop-off location (5.8%), and 11 for paid relocation (3.8%).

Various approaches exist to quantify consumer preferences for services or service attributes. For services/attributes currently offered commercially, revealed-preference is most desirable, as inferences are generated on the basis of real-world choices by consumers. For services/attributes not currently offered, an alternative is to prompt survey respondents with hypothetical questions. Stated-choice methods (Louviere et al., 2000; Krueger et al., 2016; Kim et al., 2017; Yoon et al., 2018) involve presenting respondents with hypothetical scenarios and asking how respondents would select amongst competing alternatives. Contingent valuation methods (Angell et al., 2018; Chung and Chiou, 2017; Mitchell and Carson, 1989; Rotaris and Danielis, 2018) differ from this approach in that respondents are directly asked to state their monetary valuation of a given service/attribute. As noted in the listing earlier in this section, three types of approaches were employed in this study to gather information about consumer preferences for logistics management mechanisms. First, respondents were asked about their general willingness to participate in each of the mechanisms. Respondents were then prompted with specific monetary values of each of the four mechanisms and asked how likely they would be to use them under the specified pricing. Third, respondents were asked to directly state (in open-ended format) their willingness-to-pay/accept value for each of the mechanisms (i.e. the price level at which they would use it).

For each of the four relocation mechanisms, a majority of respondents report they would ‘possible or definitely’ use it, with the highest rate for alternate-drop-off location (57%) to be and paid relocation the lowest (40%). When respondents were prompted with suggested specific price values (e.g. $7.00 for vehicle delivery) and asked whether or not they would use the relocation mechanisms at those price points, the ordering of willingness-to-participate remains similar to when respondents were asked this question without being prompted with specific prices (with vehicle delivery the lowest and alternate-drop-off the highest. The survey protocol did not prompt respondents to consider specific values of additional walking distance for the alternate-pick-up/drop-off location mechanisms. This design therefore does not provide information regarding response to the amount of walking distance, and WTP/WTA for these two mechanisms should be interpreted as general rather than dependent on specific values of prospective walking distance. This limitation may mean that there is unknowable divergence (error and/or bias) between the WTP/WTA values we report and the “true” WTP/WTA values for alternate pick-up/drop-off locations (which cannot be identified from our survey data).

The literature contains two studies (Shaheen et al. (2018) and Herrmann et al. (2014)) with empirical findings on willingness to participate in two of the FFCS relocation mechanisms (alternate-pick-up and drop-off locations) suitable for direct comparison with our findings. When we compare these studies’ findings with our results, we find that the results in the prior literature show higher willingness to participate in user-based relocation (85% for alternate-pick-up location in Herrmann et al. (2014) and 85% for drop-off in (Shaheen et al., 2018), compared to 60% and 65%, respectively, in our study; however differences in question wording should be noted). The discount offered in our study is the lowest among the three (10% in this study, and 33% off for alternate-pick-up location in Herrmann et al. (2014) and 10-minute credit for 15-minutes alternate-drop-off location in Shaheen et al. (2018), and Shaheen et al. (2018) show increasing willingness-to-participate with increasing size of incentive. It is therefore reasonable that our respondents would report lower acceptance of these two incentivisation mechanisms. Finally, our respondents report preferring the alternate-drop-off location mechanism to the alternate-pick-up location option, which is consistent with the findings of Shaheen et al. (2018).

4. Results and discussion

This section first presents analysis of the times-of-week that respondents report experiencing vehicle unavailability, and then results of linear regression models of WTP/WTA for each of the four incentivisation mechanisms. Following exclusion of partial and incomplete responses, the effective sample size for the regression analysis presented in Section 4.3 is n = 292.

Of the three sets of WTP/WTA questions that elicited user preferences regarding the logistics management mechanisms (general willingness to participate on a Likert scale, willingness to participate at a specific prompted price point [also on a Likert scale]), and the open-ended WTP/WTA in units of currency or percentage discount; see Section 3), we present results from analysis of the open-ended WTP/WTA responses. This decision was based on the considerations that the direct, open-ended elicitation of WTP/WTA values provides the richest format of data on the research question, and provides elasticity values in units of currency (rather than Likert-scale units) that directly enable revenue-maximisation decisions by operators (NB: responses to all three

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1 Example question format: Based on the idea of alternate-pick-up location, please select the number (1 for ‘I would definitely not use this’ and 5 for ‘I would definitely use this’) that best reflects your opinions.

2 Example question format: Normally, trips cost $0.55/minute. What discount on the per minute price would you need to pick up a car share vehicle that is further away from you (please specify a dollar value)?

3 Example question format: Normally, trips cost $0.55/minute. If the price is $0.49/minute after the discount for picking-up/dropping-off a car share vehicle at an alternate location that is less convenient to you, how likely would you use the service?

4 Question structure in Shaheen et al. (2018) and Herrmann et al. (2014); Shaheen et al. (2018): If you were to drive for 15 min in a car2go vehicle and were expecting to be near the incentive zone, would you be willing to park your vehicle within the incentive zone if you received a 10-minute credit to your car2go account? Herrmann et al. (2014): Would you book a more distant car for 10 cent/km price reduction?
| Items                              | Categories (for categorical variables) | Statistic (Mean or category size, total) | Statistic (Mean or category size, Vancouver) | Statistic (Mean or category size, Washington D.C.) | Vancouver metropolitan area [for comparison purposes, Statistics Canada (2016)] | Washington D.C. urban area [for comparison purposes, United States Census Bureau (2018)] |
|------------------------------------|----------------------------------------|------------------------------------------|---------------------------------------------|------------------------------------------------|--------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| Age                                |                                        | 43.4                                     | 51.4%                                       | 48.6%                                            | 41.0 (average); 40.9 (median)                                            | 33.9 (median)                                                                            |
| City                               | Vancouver                               | N/A                                      | N/A                                         | N/A                                              | 2,463,431                                                                | 672,319                                                                                 |
| Employment status                  | Employed                                | 83.6%                                    | 68.0%                                       | 73.3%                                            | N/A                                                                      | N/A                                                                                      |
| Car ownership                      | With a car                              | 74.0%                                    | 90.0%                                       | 78.9%                                            | 68.0%                                                                    | 64.3%                                                                                   |
| Gender (female)                    | Male                                    | 53.3%                                    | 61.3%                                       | 26.7%                                            | 32.0%                                                                    | 35.7%                                                                                   |
|                                    | Female                                  | 46.7%                                    | 38.7%                                       | 42.8%                                            | 51.2%                                                                    | 52.6%                                                                                   |
| Education level                    | Below bachelor                          | 37.3%                                    | 12.7%                                       | 25.3%                                            | 69.4%                                                                    | 43.4%                                                                                   |
|                                    | Bachelor and above                      | 62.7%                                    | 87.3%                                       | 74.7%                                            | 30.6%                                                                    | 56.6%                                                                                   |
| Personal income per year           | < $40,000                               | 15.3%                                    | 6.3%                                        | 11.0%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | $40,000-$60,000                         | 15.3%                                    | 15.3%                                       | 13.7%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | $60,000-$80,000                         | 10.0%                                    | 12.0%                                       | 11.3%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | $80,000-$100,000                        | 12.0%                                    | 12.7%                                       | 19.5%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | > $100,000                              | 24.0%                                    | 27.9%                                       | 30.2%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Prefer not to answer                    | 23.3%                                    | 36.6%                                       | 14.4%                                            | N/A                                                                      | N/A                                                                                      |
| User type                          | With only FFCS membership               | 84.0%                                    | 34.5%                                       | 59.9%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | With both FFCS and round-trip membership| 16.0%                                    | 65.5%                                       | 40.1%                                            | N/A                                                                      | N/A                                                                                      |
| FFCS Membership duration           | Have not used at all                    | 5.3%                                     | 1.4%                                        | 4.8%                                             | N/A                                                                      | N/A                                                                                      |
|                                    | < 6 months                              | 14.0%                                    | 16.2%                                       | 20.2%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | 6 months to < 1 year                    | 18.0%                                    | 16.9%                                       | 20.5%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | 1 year to < 2 years                     | 20.7%                                    | 31.0%                                       | 22.9%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | 2 years or more                         | 42.0%                                    | 34.9%                                       | 31.5%                                            | N/A                                                                      | N/A                                                                                      |
| Frequency of FFCS usage            | Have not used at all                    | 4.7%                                     | 3.5%                                        | 4.1%                                             | N/A                                                                      | N/A                                                                                      |
|                                    | Once a month or less                    | 0.0%                                     | 0.0%                                        | 0.0%                                             | N/A                                                                      | N/A                                                                                      |
|                                    | Couple times a month                    | 45.3%                                    | 31.0%                                       | 38.4%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Once a week                             | 28.0%                                    | 26.1%                                       | 27.1%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Couple times a week                     | 12.0%                                    | 22.5%                                       | 17.1%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Daily                                   | 10.0%                                    | 16.9%                                       | 13.4%                                            | N/A                                                                      | N/A                                                                                      |
| Percentage of users commuting      |                                        |                                          |                                              |                                                  |                                                                          |                                                                                          |
| primarily by carsharing            |                                        |                                          |                                              |                                                  |                                                                          |                                                                                          |
| Satisfaction level with FFCS       | On a scale of 1–10, with 10 being very | 7.29                                     | 6.63                                        | 6.0%                                             | 8.00                                                                     | 4.2%                                                                                     |
| availability                        | very satisfied and 1 very unsatisfied   |                                          |                                              |                                                  |                                                                          |                                                                                          |
| Frequency of FFCS unavailability   | Never                                   | 9.3%                                     | 4.2%                                        | 6.8%                                             | N/A                                                                      | N/A                                                                                      |
|                                    | Rarely                                  | 19.3%                                    | 19.7%                                       | 19.5%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Sometimes                               | 44.0%                                    | 36.6%                                       | 40.4%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Often                                   | 22.7%                                    | 16.2%                                       | 19.5%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Most of the time                        | 4.0%                                     | 13.4%                                       | 8.6%                                             | N/A                                                                      | N/A                                                                                      |
|                                    | Always                                  | 0.7%                                     | 9.9%                                        | 5.1%                                             | N/A                                                                      | N/A                                                                                      |
| Attitudes toward vehicle delivery  | Definitely or possibly use              | 44.6%                                    | 49.3%                                       | 46.9%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Neutral                                 | 28.7%                                    | 30.3%                                       | 29.5%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Definitely or possibly not use          | 26.7%                                    | 20.4%                                       | 23.6%                                            | N/A                                                                      | N/A                                                                                      |
| Attitudes toward alternate         | Definitely or possibly use              | 34.6%                                    | 57.7%                                       | 45.9%                                            | N/A                                                                      | N/A                                                                                      |
| pick-up location                   | Neutral                                 | 40.0%                                    | 21.8%                                       | 31.2%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Definitely or possibly not use          | 25.4%                                    | 17.6%                                       | 22.9%                                            | N/A                                                                      | N/A                                                                                      |
| Attitudes toward alternate         | Definitely or possibly use              | 54.0%                                    | 59.1%                                       | 56.5%                                            | N/A                                                                      | N/A                                                                                      |
| drop-off location                  | Neutral                                 | 29.3%                                    | 23.2%                                       | 26.4%                                            | N/A                                                                      | N/A                                                                                      |
|                                    | Definitely or possibly not use          | 16.7%                                    | 17.6%                                       | 17.1%                                            | N/A                                                                      | N/A                                                                                      |

(continued on next page)
types of questions were statistically significantly correlated, as would be expected; see Table 5).

4.1. Cluster analysis of availability issues

By combining respondents’ answers to the times-of-week that they report difficulty finding an available shared vehicle, we sought to identify whether there are distinct segments of users with different experiences regarding vehicle unavailability. We employ a k-means clustering approach (Yadav and Sharma, 2013), and in order to select the optimal number of clusters we employed the ‘elbow’ method in which the analyst reviews the amount of additional statistical information (the normalised sum-of-squares for each independent variable from each data point to the centre [mean value] of the cluster) provided by adding each marginal cluster, and seeks to identify when adding additional clusters is no longer justified (Kodinariya and Makwana, 2013). Fig. 2 shows this ‘elbow’ plot; we elected to proceed with the four-segment solution, details of which are presented in Table 6.

The first segment contains the smallest number of respondents and reports the highest level of difficulty finding vehicles during off-peak daytime on weekdays and lowest difficulty on weekends. This segment has the lowest overall satisfaction with vehicle availability and relatively low FFCS usage frequency (average of 136 uses/year).

The second segment reports availability issues during weekday peak periods and weekend daytime periods. This segment has the highest frequency of usage, and a relatively high mode share of carsharing for commuting purposes (34%, versus 24% for the full sample). The latter may explain why this segment reports experiencing unavailability during typical commuting periods.

The third segment is the largest (47% of respondents) and has the lowest FFCS usage frequency (123 uses/year). This segment shows the fewest reported experiences of vehicle unavailability, particularly during weekdays. 50% of the respondents report they have no difficulty of finding a vehicle nearby at any weekday time periods. The low average usage frequency of this segment may explain why these users experience the fewest vehicle-availability issues.

The fourth segment indicates difficulties finding available vehicles at late evenings (9 PM to midnight) on both weekdays (29%) and weekends (87%). This segment also has a high frequency of usage (230 uses/year) and the highest mode share of carsharing for commuting (38%). One possibility is that this segment of respondents may simple use FFCS frequently during late evenings, however the survey did not collect information about frequency-of-usage by time-of-day, so this cannot be known with certainty.

4.2. Correlation of the relocation mechanisms

We now investigate patterns of correlation amongst the four relocation mechanisms, with two hypotheses. First, we hypothesised that WTP/WTA values would generally be positively correlated with one another, which would imply that people willing to use any of the four mechanisms are also generally likely to use the other mechanisms. Second, we hypothesised that WTP/WTA values for the mechanisms that are functionally more similar to each other will be more strongly correlated than for mechanisms that are less similar in functionality.

Both hypotheses are supported by the data. Table 7 shows that all bi-variate correlations are positively signed, with five of the six correlations statistically significant. The largest correlation ($r = 0.71$) is between the alternate pick-up location and alternate drop-off location mechanisms, which are very closely related to each other in their impacts on the user experience. The weakest correlations are between the paid-relocation mechanism and the other three mechanisms. This is intuitive as the paid relocation mechanism requires the user to make a
new journey that they would otherwise not make, whereas the other three mechanisms involve the user somehow modifying a characteristic of a journey they would have made anyway.

4.3. Modelling results of willingness-to-pay and willingness-to-accept

We employ linear regression to analyse how willingness-to-pay/accept are associated with variables describing socio-demographics and
models ranges from $r^2 = 0.02$ to 0.22; the models with values at the upper end of this range have goodness-of-fit comparable to earlier literature where the dependent variable is open-ended WTP\(^5\). For both Model \#A and \#B, the goodness-of-fit is highest for the two alternate location mechanisms (pick-up and drop-off), and poorest for the paid-relocation mechanism. In other words, the models perform worst at predicting which users would choose to participate in paid relocation.

We performed the following tests (Greene, 2017) to determine whether the data meet the assumptions for applicability of ordinary least squares (OLS) regression:

1. **Multicollinearity:** All variables except age and age-squared are not significantly multicollinear, with variance inflation factor (VIF) less than 10. The collinearity of age and age-squared is expected due to their structural relationship, and we elected to retain both variables due to the motivation to investigate possible non-linear effects of age (see Fig. 3 and associated discussion below).

2. **Normality:** The normality of the linear regression residuals was investigated by a Shapiro-Wilk test. The residuals for each model presented in Tables 8 and 9 were found to be distributed significantly different from normality. We then transformed the dependent variables via the Box-Cox transformation, in an attempt to bring them close to normality, to reduce non-normality in the residuals. This was unsuccessful, however, due to the self-reported WTP/WTA values (generated via free-entry of a number into a form on the questionnaire, without prompting) having a large number of distinct point masses at round values (see Fig. 1.)

3. **Independence:** We tested for auto-correlation in the residuals; no issues were identified, with values of Durbin-Watson statistics for all models in the range of 2.0.

user experiences with FFCS. The dependent variables we use are the open-ended WTP values for vehicle delivery and WTA (per minute or percentage discount) values for the other three mechanisms (alternate pick-up location, alternate drop-off location and paid relocation). These four dependent variables are highlighted in bold font in the bottom four rows of Table 4.

The regression results are presented in Tables 8 and 9. We estimated two sets of models, with the first including only socio-demographic features and the second also including user experience variables (including each respondent’s segment-membership as discussed in Section 4.1). We employ the prefixes ‘A’ and ‘B’ to indicate the first and the second sets of model runs, and sequentially number willingness-to-pay/accept for vehicle delivery, alternate pick up/drop-off location, and paid relocation one through four. For example, Model \#A1 indicates willingness-to-pay for vehicle delivery with only socio-demographic features. For all models, effects with $p < 0.15$ are retained (all others are excluded); the in-text discussion that follows is limited to effects significant at the $p < 0.05$ level. The goodness-of-fit of the eight

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\(^5\) In models of WTP with similar functional form, (Bobinac et al., 2010) report $r^2$ values in the range of 0.06–0.08 (in the context of WTP for improved health outcomes [quality-adjusted life years]) and (Dorcec et al., 2018) report $r^2$ values of 0.34 (in the context of WTP for electric vehicle charging).
4. **Homoscedasticity**: We tested for the presence of homoscedasticity using the Breusch-Pagan test; no issues were identified, as determined by the p-values of regressions of the residuals against the independent variables.

5. **Linearity**: We investigated scatter plots of each of the independent variables against the dependent variables (with the exception of the binary independent variables, for which non-linearity is not an issue). With the exception of age (which is addressed below in Table 7), we did not identify possible non-linear relationships that appeared to merit incorporating non-linear effects into the analysis.

In the discussion that follows, we employ speculative language ("could", "may", etc.) to discuss possible explanations for findings that the results suggest but which cannot be unambiguously concluded by statistical analysis alone. Also, due to the departure of the self-reported WTP/WTA values from the assumed normal distributions (see point #2 in numbered list immediately above), and despite efforts to transform the values to mitigate this issue, results should be interpreted with this borne in mind.

By adding user-experience, the overall goodness-of-fit improves for all model runs from Tables 8 and 9 after penalizing for the added variables (in the adjusted $r^2$ metric), and most socio-demographic effects become insignificant when the user-experience variables are added. This suggests that the user-experience variables are in general stronger predictors of WTP/WTA than socio-demographics. The variable with the strongest and most significant influence on the willingness-to-pay/accept (for all four mechanisms) is the frequency at which a respondent has experienced shared vehicle unavailability. This is intuitive, as direct personal experience with unavailability would be expected to be associated with a high willingness to participate in mechanisms to improve reliability. Frequency of vehicle unavailability is positively associated with all four WTP/WTA variables, which indicates if a user reports encountering vehicle unavailability frequently, the user has a high WTP for vehicle delivery, and also requires a larger discount from an operator asking him/her to change their intended pick-up/drop-off location.

Model A1 in Table 8 shows that the only socio-demographic effects that are significant in predicting WTP for delivery of a FFCS vehicle are age, city of residence (Washington versus Vancouver), and private car ownership. Owning a personal vehicle is strongly positively associated with WTP for FFCS-vehicle-delivery (+ $2.61 per each delivery), which could indicate that car-owning people have relatively tight scheduling requirements and are thus willing to pay relatively large amounts for a FFCS vehicle to be delivered to them. Car ownership is only statistically significant for WTA for alternate pick-up locations: Owning a personal vehicle is associated with a larger required discount. This result is intuitive, as private car owners have more travel options, and they hence may be less willing to change their shared-car pick-up locations.

We modelled the effect of age with an additional age-squared term to test for the presence of non-linearity; Fig. 3 shows the result that older age is associated with lower WTP for vehicle delivery and smaller required incentives to participate in the alternate pick-up/drop-off locations (age does not have significant impact on WTA for paid relocation). This finding was counter to our expectations, as we had theorised that older users may more willing to pay for vehicle delivery and less willing to change their vehicle pick-up/drop-off locations. We therefore tested the bi-variate correlation of age and income to determine whether the effect attributed to age might be a spurious artefact of a relationship between income and age, however we found this correlation to be insignificant ($r = 0.06; p = 0.31$). To further investigate this finding, we then examined the bi-variate correlations between age and each of the four dependent variables; we found statistically significant bi-variate correlations with the three mechanisms corresponding to Models A1, A2 and A3 ($r = -0.15, -0.27, -0.33$, with $p = 0.01, < 0.01, < 0.01$, respectively) but not Model A4 ($r = +0.02, p = 0.80$), which corroborate the ceteris paribus parameter estimates shown in Table 8. Thus, our result that older FFCS users have a lower WTP for vehicle delivery and require smaller incentives for alternate pick-up/drop-off locations appears to be a robust finding (at least within this survey dataset).

As would be expected on the basis of the strong correlation between WTA for alternate pick-up and drop-off locations (see Section 4.2), Models #A2 and A3 show similar patterns of parameter estimates. Table 9 shows that all socio-demographic variables that are retained in the models (using the $p < 0.15$ criterion) have the same sign after the addition of the user experience variables, and that only age and car ownership remain statistically significant in both sets of model runs.

Models B3 and B4 show that high frequency of FFCS usage is positively associated with willingness to participate in the alternate drop-off location and paid relocation mechanisms. The reported frequency of experiencing FFCS vehicle unavailability is also significant in all models in Table 9, however all segment-membership variables relating to time-of-week that unavailability is experienced are insignificant (with the smallest p-value of 0.11). This suggests that experiencing unavailability at all matters more than when unavailability is experienced.

5. **Summary and conclusions**

The inherent spatio-temporal volatility of free-floating shared-mobility fleets is a major logistical challenge. In this study we quantified user preferences towards four prospective mechanisms for managing fleet positioning, via a survey of free-floating carsharing users. We present new findings of factors associated with choosing to use various relocation mechanisms, and in the two instances that our results can be compared with earlier literature (Herrmann et al., 2014; Shaheen et al., 2018), we demonstrate that the findings are broadly consistent. Specifically, we find lower rates of participation, but for smaller sizes of incentives, and we find that alternate vehicle drop-off locations are generally preferred to alternate pick-up locations.

We found that between 40% and 57% of respondents would
probably’ or ‘definitely’ use each of the four incentivisation mechanisms for user participation in vehicle positioning. The lowest share (40%) is willing to participate in paid relocation. The highest share (57%) is willing to drop off a FFCS vehicle they are using in a location that is less convenient to them personally but more desirable to the system operator. We also find that willingness to participate in this “drop-off” incentivisation is strongly positively correlated ($r = 0.71$) with willingness to pick up a FFCS vehicle in a less convenient alternate location. Users’ willingness to participate in the other mechanisms are also positively correlated with one another, with lower strengths of correlation (most but not all are significant).

Multivariate analysis of willingness to participate in these four mechanisms finds that variables describing users’ experience with FFCS are generally stronger predictors of willingness-to-pay/willingness-to-accept than are socio-demographic variables. We performed a k-means cluster analysis of the times-of-week that users report having difficulties with vehicle unavailability. We found that these “times-of-week” variables were not significantly associated with willingness-to-pay/accept for any of the four mechanisms, however an aggregate measure of the frequency in which a respondent has encountered vehicle unavailability is highly significant in all four models (with positive impacts on willingness to pay for vehicle delivery and negative impacts on willingness to participate in other three mechanisms). We also found that, counter to our a priori expectations, older age is associated with lower willingness to pay for vehicle delivery and smaller required incentives to participate in alternate pick-up/drop-off vehicle relocation mechanisms.

We now conclude with a brief discussion of future research needs. First, research is needed to establish whether WTP and WTA vary in linear or nonlinear ways with incentive size, and therefore how to optimally set the size of incentives. Second, further empirical results are needed to confirm or refute our finding that older age is generally associated with requiring smaller incentives to participate in vehicle relocation. Third, other possible mechanisms for optimising FFCS fleet logistics exist beyond those considered in this study (e.g. secondary markets (Le Vine, 2014), virtual queuing (McGinley et al., 2014), and reservation mechanisms (Boyaci et al., 2017)), and evidence of consumer preferences for them are needed – including how they may interact if offered concurrently. Fourth, the possibility of FFCS users’ responding strategically (rather than myopically) to incentivisation will require further research, for instance in game theoretical frameworks in which operators and users interact with one another on the basis of their expectations of future behaviour. Finally, the survey data collection was undertaken prior to the covid-19 pandemic which is occurring at the time of publication. Given the profound impacts the pandemic is having on urban transport systems, it is urgently important to understand how FFCS users’ preferences for both crowdsourced and centrally-administered fleet-management mechanisms are evolving.

It is hoped that this study will be useful to both FFCS operators and public sector policy-makers, as they work to optimise the benefits from increasing the scale and coverage of shared-mobility systems. Specifically, better understanding of consumer preferences towards various user-based vehicle relocation mechanisms is a necessary requirement for implementing incentivisation mechanisms that maximise the efficiency of these mobility services.

CRediT authorship contribution statement

Chenyang Wu: Methodology, Conceptualization. Scott Le Vine: Methodology. Sandra Philips: Conceptualization, Supervision. William Tang: Methodology. John Polak: Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to
| Attribute                      | Model #B1 (willingness-to-pay for vehicle delivery, $) | Model #B2 (willingness-to-accept for alternate pick-up location, $/min discount) | Model #B3 (willingness-to-accept for alternate drop-off location, $/min discount) | Model #B4 (willingness-to-accept for paid relocation, % discount per month) |
|-------------------------------|------------------------------------------------------|-------------------------------------------------------------------------------|-------------------------------------------------------------------------------|------------------------------------------------------------------------|
| Constant                      | -10.54 < 0.01                                        | 0.56 < 0.01                                                                     | 0.54 < 0.01                                                                     | 0.19 < 0.01                                                             |
| Age                           | *                                                     | -0.01 < 0.01                                                                     | -9.8E-5 < 0.01                                                                  | *                                                                      |
| Age squared                   | *                                                     | 1.14E-4 < 0.01                                                                   | *                                                                              | *                                                                      |
| City                           | *                                                     | *                                                                              | *                                                                              | *                                                                      |
| Employed                      | *                                                     | *                                                                              | *                                                                              | *                                                                      |
| Car ownership                 | 1 for having a private vehicle                        | 0.04                                                                           | 0.04                                                                           | *                                                                      |
| Education                     | *                                                     | *                                                                              | *                                                                              | *                                                                      |
| Income                        | *                                                     | *                                                                              | *                                                                              | *                                                                      |
| User type                     | *                                                     | *                                                                              | *                                                                              | *                                                                      |
| Membership duration           | *                                                     | *                                                                              | *                                                                              | *                                                                      |
| Frequency of usage            | *                                                     | *                                                                              | 1.79E-4 < 0.01                                                                  | 1.55E-4 0.05                                                          |
| Satisfaction of vehicle       | 1 for very dissatisfied and 10 for very satisfied     | 1.14 < 0.01                                                                     | *                                                                              | *                                                                      |
| availability                  | *                                                     | *                                                                              | *                                                                              | *                                                                      |
| Frequency of vehicle          | 1 for never and 6 for always                          | 2.67 < 0.01                                                                     | 0.02                                                                           | 0.02                                                                    |
| unavailability                | *                                                     | *                                                                              | *                                                                              | *                                                                      |
| Segment 1st                   | 1 for belonging to the first segment                  | *                                                                              | *                                                                              | *                                                                      |
| Segment 2nd                   | 1 for belonging to the second segment                 | 0 (fixed)                                                                       | 0 (fixed)                                                                       | 0 (fixed)                                                             |
| Segment 3rd                   | 1 for belonging to the third segment                  | *                                                                              | 0.03                                                                           | 0.13                                                                    |
| Segment 4th                   | 1 for belonging to the fourth segment                 | 2.62 0.11                                                                       | *                                                                              | *                                                                      |
| $r^2$                         | 0.13                                                  | 0.15                                                                           | 0.22                                                                           | 0.05                                                                   |
| Adjusted $r^2$                | 0.12                                                  | 0.14                                                                           | 0.20                                                                           | 0.04                                                                   |
| p-value of F-test             | < 0.01                                               | < 0.01                                                                          | < 0.01                                                                          | < 0.01                                                                 |
influence the work reported in this paper.

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Fig. 3. Age vs willingness-to-participate.
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