Projected Prevalence of Car-Sharing in Four Asian-Pacific Countries in 2030: What the Experts Think


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Abstract

This paper presents a “big-picture view” for policymakers and related stakeholders regarding the future development of car-sharing services. Car-sharing has the potential to significantly disrupt the personal mobility market. Thus, understanding their market penetration and implications is urgently needed. Previous studies in this domain have predominantly focused on the views, opinions, and preferences of consumers. In this study, we complement the current demand modelling research on car-sharing by applying an expert elicitation and aggregation technique that relies on transport experts’ opinions to investigate the role of car-sharing in the future. Specifically, based on the opinions of mobility suppliers, this research elicits experts’ judgment from across government, industry, and academia to gain insights into the future of car-sharing markets in four countries - Australia, Malaysia, Indonesia, and Thailand. The analysis reveals that, from a mobility supplier’s perspective, energy and vehicle prices will not have a statistically significant impact on the future adoption of car-sharing. The results also show that the more knowledgeable an expert is, the more pessimistic they are about the market penetration of car-sharing in 2016, and the more optimistic they are about the prevalence of car-sharing in 2030.

Keywords: Car-sharing, expert elicitation, Bayesian truth serum, demand modelling, survey, market

1. Introduction

Numerous resources in modern society are under-utilized. This is particularly the case within the transport sector, where private vehicle ownership dominates the set of mobility choices in spite of the fact that a typical car remains unused for approximately 95% of the day [Shoup, 2005]. This particular example of inefficiency within our current transport system highlights the potentially significant benefits that new mobility services present to policymakers who aim to reduce the environmental and health impacts of congestion, as well as improve the overall liveability of urban environments.

Car-sharing is a mobility service that allows members to have short-term access to automobiles [Duncan, 2011]. After signing up for a vehicle-sharing service that allows members to use a variety of vehicles, one can reserve a vehicle for a specific trip. The main aim of car-sharing is to provide individuals with a mobility solution that requires lower responsibilities and smaller associated costs than vehicle ownership (e.g., initial capital cost, fuel, maintenance, insurance, etc.). Convenience and affordability are core features of car-sharing, and it is therefore of particular interest to consumers who only occasionally use a vehicle or cannot afford to own a private vehicle [Litman, 2000].

Over the past decade, researchers have investigated a range of issues related to car-sharing, including understanding consumer preferences, identifying barriers and opportunities, and forecasting future market potential. This study contributes to this discussion by applying a unique approach within the car-sharing literature to elicit experts’ opinions. This, in turn, will shed light on what transport experts expect the future of the car-sharing marketplace to look like in Australia, Malaysia, Indonesia and Thailand over the next 15 years.
When predicting future events, policymakers, researchers, and industry stakeholders need to account for the uncertainty associated with the evolution of a wide range of variables (Morgan et al., 1992). Predicting the car-sharing market potential is fraught with challenges because it involves expertise and knowledge from a broad range of fields, including government, academia, and industry. One way to accommodate its multidisciplinary nature is to obtain cross-sectional knowledge by eliciting the opinions of experts who have informed views about the likely future evolution of the mobility marketplace and are aware of the relevant factors. This approach has been frequently and successfully used in studies across a wide range of disciplines, such as forecasting national economic growth (Gordon and Helmer, 1964), analyzing the risk associated with nuclear waste storage (Dewispelare et al., 1995), forecasting climate change (Morgan et al., 2001), assessing environmental health (Knol et al., 2010), and modelling shipping accidents (Zhang and Thai, 2016). However, eliciting experts’ opinions presents two well-known challenges: experts may not have the appropriate incentives to reveal their true beliefs, and some experts may be better informed than others. The Bayesian Truth Serum (BTS), proposed by Prelec (2004), is an analytical solution designed to address these two challenges. More discussion on BTS is provided later.

Mainly using BTS, this study forecasts market penetration (measured as the trip proportion) of car-sharing in four countries. More specifically, the unweighted or average aggregated (using the majority rule) forecasts are compared with the BTS-weighted/aggregated ones. Factors influencing experts’ predictions and changes in car ownership are also analyzed. This specific investigation into the future of the car-sharing market was part of a larger project aiming to build market intelligence regarding the mobility market in Asia-Pacific countries over the next 15 years. The scope of the overarching project encompassed forecasting uptake of different mobility services, and the potential impacts of different policies and market variations, such as fluctuations in energy prices. The ultimate aim of this broader project is to use the information obtained through this research piece, in addition to other consumer-focused studies, to generate a series of likely mobility market scenarios from 2016 to 2030 for Thailand, Indonesia, Malaysia, and Australia. In the context of the larger project, we intend to compare the results obtained through elicitation of experts’ opinions with those obtained using more conventional consumer survey techniques (including stated preference tasks) at a later date in order to better understand the relative merits and pitfalls of each approach.

This paper continues by providing an overview of the car-sharing literature, particularly car-sharing demand modelling in Section 2. Section 3 presents the methodology employed in this study, specifically the elicitation method (i.e., the BTS) developed by Prelec (2004). This is followed by the results which are documented in Section 4. Finally, Section 5 concludes with a discussion of this study’s main contributions and limitations, as well as topics that warrant further investigation.

2. Literature review

The following section provides an overview of the car-sharing literature with a focus on demand modelling.

2.1. The case for car-sharing

Globally, vehicle ownership continues to grow. More vehicles will be manufactured as developing countries keep improving the living standard of their citizen, and the improved features of private vehicles such as comfort, convenience, and prestige will lead people to move to motorized vehicles as long as economically feasible (Wright and Fulton, 2005; Dargay and Gately, 1999; Dargay et al., 2007; Fulton and Eads, 2004; Bradshaw, 2010). As a consequence, the increasing ownership and usage of vehicles are leading to numerous social, economic, and environmental issues (Schuster et al., 2005; Frank et al., 2010; Nordlund and Garvill, 2005; Booth et al., 2000; Steg, 2005). In response to this situation, the potentially positive effects of car-sharing are of interest to policymakers and researchers. Car-sharing programs have the potential to reduce automobile usage and personal vehicle ownership, as well as encourage individuals to use public transport/cycling/walking more frequently (Martin and Shaheen, 2011). Ultimately, a more-efficient utilization of urban mobility services can reduce the total number of vehicles on the road, lead to vehicles being used more efficiently, reduce idling time and, in turn, reduce the need for parking spaces (Mitchell et al., 2010).
2.2. History of car-sharing

Car-sharing began in the mid-20th century. The first trial was launched in Zurich, Switzerland, in 1948 and expanded during the following decades to other European countries, including France, Netherlands, Sweden and others. In North America, car-sharing started with two projects: Mobility Enterprise, conducted by a Purdue University research group; and Short-Term Auto Rental (STAR) in San Francisco in the early 1980s (Shaheen and Cohen, 2007). The first car-sharing programs in Asia were established in Singapore in 1997, followed by Japan in 1998, and more recently in Israel, China, South Korea, and Malaysia between 2006 and 2009 (Shaheen and Cohen, 2013).

The car-sharing industry has been expanding rapidly since its first appearance in Europe and now serves people in more than 30 countries across five continents. The worldwide members of car-sharing programs increased from 346,610 in 2006 to around 5 million in 2014 (Shaheen and Cohen, 2013; Greenblatt and Shaheen, 2015).

2.3. Forecasting the market penetration of car-sharing

A number of studies have either used data from car-sharing operators or conducted surveys on car-sharing members to identify the characteristics of consumers. Car-sharing users tend to be well-educated individuals, who earn higher than average income, and are aged between 25 and 44 (Prettenthaler and Steininger, 1999; Litman, 2000; Loose et al., 2006; Efthymiou et al., 2013; Kim et al., 2017). While understanding the existing adopters of car-sharing programs is important, it is crucial to predict future demand. As such, one of the main focuses of car-sharing research has been to forecast future market demand. A summary of car-sharing forecast literature, including the chosen methodology, factors, or variables considered, study area, and market potential prediction are summarized in Table 1.

As shown in Table 1, several different approaches are described in the literature to forecast the future market penetration of car-sharing, and almost all studies are carried out from the customer’s perspective, except for two studies by Shaheen and associates. In Shaheen et al. (2006) and Shaheen and Cohen (2013), the authors elicited car-sharing experts’ opinions to predict the future outlook of the car-sharing industry regarding market growth and development. However, they only focus on a small sample of experts from the car-sharing industry i.e., 25 experts, representing 25 countries. As mentioned previously, because of its multidisciplinary nature, expertise and knowledge of experts from different sectors (industry, government, and academia) are needed in order to more-accurately and more-comprehensively understand the future market penetration of car-sharing.

This issue has been addressed in this study. By using the BTS method we are able to gain valuable insight into the market from supply-side experts in the field and obtain more reliable estimates of the car-share market potential over the next 15 years. Details on elicitation of experts and the BTS methodology are provided in the next section.
<table>
<thead>
<tr>
<th>Study</th>
<th>Method</th>
<th>Attributes/variables</th>
<th>Study area</th>
<th>Predicted market potential</th>
</tr>
</thead>
</table>
| Prettenthaler and Steininger (1999) | Survey and field experiment | • Distance travelled per year  
• Cost based on distance travelled  
• Time value (waiting)  
• Volume of cars | Austria | Market potential is predicted as 9%; only 1.5% of participants joined during the 2-month car-sharing test in 1994. |
| Schillander (2003) | Questionnaire | • Possession of a driver’s license  
• Home location  
• Time of work or school trip | Sweden | Car-sharing potential was estimated as 5.6% based on a survey in 2002. |
| Schuster et al. (2005) | Monte Carlo simulation | • Cost saving (depreciation, insurance, repair, fuel, membership fee, time cost, etc.) | Baltimore, Maryland | 4.2% to 14.8% of total vehicles could be shared under different scenarios and schemes. Simulated using data collected in 2001. |
| Shaheen et al. (2006) | Expert elicitation with existing operators | • N/A | US and Canada | Based on a survey in 2005, business market could reach 22% and 15% in the US and Canada in five years. |
| Catalano et al. (2008) | Stated preference | • Travel duration  
• Trip cost  
• Parking time  
• Access time  
• Political scenario | Palermo city, Italy | By controlling private vehicle usage, the car-sharing market share could rise up to 10%. The year for the stated-preference experiments was unclear; demographic and public transport-related data were based on 2001. |
| Zheng et al. (2009) | Stated preference | • Vehicle ownership  
• Environmental concern  
• Fuel cost concern  
• Parking cost  
• Familiarity of car-sharing | University of Wisconsin | With different walk access time and monthly fee, between 18% and 30% of individuals in this university would use a car-sharing service. Based on the stated-preference experiments in 2008. |
| Shaheen and Cohen (2013) | Expert elicitation with existing operators | • N/A | Worldwide | Among 21+ individuals in metropolitan areas, the growth potential between 2010 and 2015 was 4.2% in Asia, 3% in Australia; 2.9% in European cities, 2% in South America, and 10% in North America. |
3. Methodology

Predicting future economic and social developments is inherently difficult. A wide range of complex and difficult-to-anticipate factors play different roles in shaping future trends. Experts’ opinions can be useful for understanding relevant ongoing trends and anticipating future events given existing political, economic, and social constraints.

Predicting the market potential of car-sharing programs throughout the Asia-Pacific region in 2030 presents a similar type of challenge. This paper uses experts’ opinions to piece together predictions about the future of car-sharing and mobility-related trends in these regions. As shown in Fig. 1, a two-phase approach is used to elicit these opinions and perspectives: (1) three well-defined scenarios were used to stretch the thinking of survey participants (experts) and to help focus their minds on the emerging trends in the market over the next 15 years, and (2) BTS (Prelec, 2004) was applied to reveal respondents’ true beliefs and to give estimate weights proportional to the reliability of the experts’ knowledge. In addition, experts’ opinions regarding future energy price evolution are aggregated by Principal Component Analysis (PCA) to generate an index representing overall change of energy price in the future. The next subsections explain the survey design and how scenarios, BTS, and PCA were used.

Figure 1: Methodology

3.1. Survey

To record experts’ opinions, an online survey was developed based on transport- and mobility-related literature and industry reports. The survey and corresponding delivery strategy were put together according to the principles outlined in Dillman (2000)’s “Tailored Design Method”.[1] Prior to launching the survey in August 2015 the questionnaire was pre-tested and amended based on discussions and feedback provided by several industry professionals, government officials, and academics. Consisting of 55 questions, the survey was divided into four main sections: (1) screening questions to determine respondents’ backgrounds, (2) eliciting their opinions about transportation in 2016,
capturing their opinions about transportation in 2030, and (4) asking questions about the respondents’ experiences with using the online survey.

Participants were identified and recruited based on advice and recommendations from government authorities and industry experts in each of the four countries included in the survey - specifically, Australia, Indonesia, Malaysia, and Thailand. These pre-eminent, domain-specific experts were selected based on their qualifications and professional experience in the energy, automotive, and other transport-related industries in each of the four countries. Their professional positions included high-ranking job titles, such as “President of Industry Association,” “Chief Executive Officer,” and “Director.”

Personal emails were sent to each of the experts inviting them to participate. A total of 300 experts were contacted in late April of 2015 - 59 from Australia, 103 from Malaysia, 80 from Indonesia, and 58 from Thailand. Excluding 21 bounced emails, 73 out of 279 completed responses were received, with participating experts approximately evenly distributed across the three sectors: 38.36% from academia, 28.77% from government, and 32.88% from industry. The overall response rate and the response rate by nations are summarized in Table 2. The number of respondents from the four countries was relatively balanced, with only slightly fewer participants from Thailand.

### Table 2: Response rate

<table>
<thead>
<tr>
<th>Country</th>
<th>Number of Experts Invited</th>
<th>Number of Responses</th>
<th>Response Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>59</td>
<td>22</td>
<td>37.29%</td>
</tr>
<tr>
<td>Indonesia</td>
<td>103</td>
<td>21</td>
<td>20.39%</td>
</tr>
<tr>
<td>Malaysia</td>
<td>80</td>
<td>17</td>
<td>21.25%</td>
</tr>
<tr>
<td>Thailand</td>
<td>58</td>
<td>13</td>
<td>22.41%</td>
</tr>
<tr>
<td>Overall</td>
<td>279 (300 sent, 21 bounced)</td>
<td>73</td>
<td>26.16%</td>
</tr>
</tbody>
</table>

The majority of respondents (67.13%) had a post-graduate degree, representing a highly educated sample. The sample consisted of a mix of male and female experts, however, dominated by male experts (87.67%). 69.87% had five or more years of experience working in a transport-related sector (almost half of the respondents indicated that they had more than ten years of experience). A summary of the respondent characteristics is provided in Table 3.

In order to apply the BTS technique respondents are required to not only provide their answer but also predict how other experts would answer the same question (the prediction of the sample distribution of endorsements). The following questions are extracted from our survey as examples:

**Q1a. What do you think the market penetration of car-sharing programs will be in 2030?** (A. 0% to 5%; B. 6% to 10%; C. 11% to 25%; D. 26% to 50%; E. 51% or more)

**Q1b. What do you think the distribution of responses from ALL OTHER EXPERTS will be regarding the market penetration of car-sharing programs in 2030?**

<table>
<thead>
<tr>
<th>Market penetration</th>
<th>0-5%</th>
<th>6-10%</th>
<th>11-25%</th>
<th>26-50%</th>
<th>51% or more</th>
<th>Total%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Responses’ distribution</td>
<td>10%</td>
<td>20%</td>
<td>70%</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
</tr>
</tbody>
</table>

After answering **Question 1a**, experts move to **Question 1b**. An expert may state for instance: “10% of the experts will choose response A, 20% of them will endorse response B, 70% are in favor of option C, and no one will choose the remaining options (D and E)”, ensuring that these response predictions add up to 100%. The answers to this two-part question are then used to compute a BTS score for the participant. Within a participant’s country, participants were financially rewarded in proportion to their BTS scores. Participants received between AU$50 and AU$200 (or equivalent in the participant’s local currency as at the date of distribution) as either a gift card (as determined by the promoter) or money transfer. Additionally, all participants were provided with a detailed report (electronic copy) describing the detailed findings from the survey once all surveys and analysis were completed, along with all de-identified scores.
The transportation and mobility sectors have recently experienced many changes in the form of new technologies, the availability of other travel modes, the pressure to reduce carbon emissions, and the urgency for environmental sustainability. These changes are likely to continue and increase in the future, and could potentially have significant effects on the future of mobility. Anticipating changes and identifying future trends in the long-term, however, is challenging and complex. For questions regarding mobility in 2030, participants were required to make complex value judgments about a very distant future in the presence of uncertainty.

We used scenarios as a mechanism to help respondents to think about the future and to consider the deeper underlying trends that might impact the car-sharing and mobility markets between now and 2030 (Van der Heijden, 2005). Scenarios are essentially internally consistent stories about what the future might be like (Schwartz, 1996). Respondents were shown three videos that each summarized a high-profile and publicly available scenario about the future. The content in these scenarios delivered via video was created by two organizations that are well known for their scenario planning efforts: Royal Dutch Shell (Royal Dutch Shell, 2015) and the International Energy Agency (International Energy Agency, 2015). Three particular scenarios were presented to participants, specifically “Mountains,” “Oceans” from Shell, and “New Policies” from the IEA. These particular scenarios were chosen for two reasons. First, although Shell’s scenarios are widely trusted and used extensively by a broad range of organizations around the
Table 4: Summary of three scenarios used to stretch survey participants’ thinking to 2030

<table>
<thead>
<tr>
<th>Scenario Name</th>
<th>Outline of Political and Environmental Landscape</th>
</tr>
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<tbody>
<tr>
<td>&quot;Mountains&quot; (Royal Dutch Shell)</td>
<td>• Political influence remains concentrated in the hands of the currently powerful.</td>
</tr>
<tr>
<td></td>
<td>• Natural gas core global energy supply.</td>
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<tr>
<td></td>
<td>• The environmental pressure is abated by decreasing coal use, slower economic growth, and other technologies.</td>
</tr>
<tr>
<td></td>
<td>• Global natural gas prices converge to a lower level.</td>
</tr>
<tr>
<td></td>
<td>• Oil prices remain moderate on average.</td>
</tr>
<tr>
<td></td>
<td>• Decision-makers recognize the immediate need of actions to secure stable and affordable electricity supplies and to reduce emissions from urban transport</td>
</tr>
<tr>
<td>&quot;Oceans&quot; (Royal Dutch Shell)</td>
<td>• Globalization strengthens with contribution of developing countries.</td>
</tr>
<tr>
<td></td>
<td>• High oil and gas prices.</td>
</tr>
<tr>
<td></td>
<td>• World faces energy stresses.</td>
</tr>
<tr>
<td></td>
<td>• Liquid fuels and coal plays significant role until the latter part of the century when solar overtakes.</td>
</tr>
<tr>
<td></td>
<td>• CO2 emissions are particularly high until the combination of biomass, solar and carbon capture and storage technologies work together to control it.</td>
</tr>
<tr>
<td>&quot;New Policies&quot; (IEA)</td>
<td>• Global GDP and population growth are estimated to be 3.6% and 0.9% between 2011 and 2035.</td>
</tr>
<tr>
<td></td>
<td>• Global population could reach 8.7 billion by 2035.</td>
</tr>
<tr>
<td></td>
<td>• New carbon schemes, with increasing price, will be gradually applied to industries.</td>
</tr>
<tr>
<td></td>
<td>• Electricity price also projected to increase for residents worldwide.</td>
</tr>
<tr>
<td></td>
<td>• Average crude oil prices for 2035 is $128 per barrel.</td>
</tr>
<tr>
<td></td>
<td>• Fuel subsidies will be phased out in ten years for net-importing countries.</td>
</tr>
</tbody>
</table>

For discussions about the future of energy and transportation (Van der Heijden [2005]), we wanted to balance their view with a scenario created by a source other than a large energy company motivated by profit and shareholder value. Second, we selected scenarios that collectively presented participants with a range of different perspectives and alternative future realities, while minimizing overlap that might have occurred between the two organizations’ respective scenarios. High-level summaries of each of the three scenarios are shown in Table 4.

The scenarios presented medium- to long-term outlooks, extending to government policies, energy demand, fossil fuel consumption, the rise of renewable energy sources, carbon emissions, energy technologies, and energy subsidies. It is important to note that the scenarios are not an attempt to accurately predict the future in and of themselves; instead, they offer several different future outlooks and plausible versions of the changes that might occur in the future (Schwartz [1996]), thereby facilitating thinking and challenging participants’ existing assumptions of the energy and environmental landscapes. The exercise aimed to expand respondents’ thinking to develop a range of possible outcomes and evaluate how these outcomes might affect the transportation and mobility sectors in 2030. To faithfully put forward the information in each of the three scenarios, without introducing any bias from our team, the summaries shown to respondents for each scenario were based on an almost verbatim copy of the summaries offered by each of the respective authoring organizations.

3.3. Eliciting and aggregating experts’ beliefs with the Bayesian Truth Serum

Eliciting and aggregating experts’ beliefs to form meaningful views on an issue is difficult. When eliciting experts’ opinions, one may face situations where experts do not have a sufficient incentive to be truthful, either because of social/hierarchical pressures (e.g. in group settings) or because they may use answers strategically to influence the survey results. Even considering situations when experts are truthful, they typically do not have the same quality of information; some experts may have superior knowledge or insights into how to interpret existing facts. Simple aggregation of experts’ answers may fail to identify the best experts in the group.

The shortcomings of existing methods are well known. Normal surveys using a majority rule suffer from the absence of incentives for the respondents to reveal their true beliefs and from the absence of criteria to assess the quality of the answers. Previous studies have revealed that the limitation of the “one person, one vote” approach, which counts opinions equally often leads to a result that favours shallow information (Dalkey et al. [1969] Seaver [2005]).
Bayesian Truth Serum (BTS), a method to elicit truthful opinions from experts and to aggregate them in a way that gives a greater weight to more informed opinions.

BTS is an incentive-compatible scoring rule used to elicit honest or true subjective beliefs from respondents. It can be applied in situations where the intrinsic truth is unattainable. Its strength is that it does not require the researcher to know the true answer to incentivise respondents to answer truthfully. Furthermore, the BTS score helps to rank a sample of experts as a function of the likely accuracy (truth) of their opinions. The score can then be used to produce a weighted estimate, where greater weight is assigned to those experts who are more likely to have the honest and correct opinion about the question asked. The BTS has been successfully applied in many studies, and there is no shortage of examples in existing research. Weaver and Prelec (2013) showed that BTS effectively eliminates untruthful answers by administering a recognition survey that contained a list of terms (i.e., brand names), and from which 47 terms were real and 24 were fake or did not exist. Respondents were divided into four groups: control, over claiming, BTS, and BTS with over claiming, and were asked to claim whether or not they recognized each of the terms in the survey. The results show that compared to the control group (58% real claim and 20% fake claim), respondents from the over claiming group (incentive positively correlated with the number of terms they recognized) tended to exaggerate the terms they knew (71% real and 42% fake). However, the two BTS groups (BTS only and BTS plus over claiming) both reported 14% of the fake terms recognized, which is significantly lower than the 20% and 42% reported by the control and over claiming groups. Both BTS groups reported recognizing 57% of the real terms, which is about the same level as the control group (58%). Furthermore, on average, respondents in the BTS groups spent more time than in other groups, indicating they took the questions more seriously, thus gave answers with a higher quality. As another example, Miller et al. (2014) showed that BTS allows instructors to identify participants with greater expertise by applying BTS to students in a university design course. A positive correlation between the BTS scores (calculated in the first week) and the students’ design outcomes four weeks later was found. Also, Howie et al. (2011) conducted a BTS survey to forecast the adoption rate of a new medicine before its launch, and concluded that, compared to the standard reference model, BTS improves the predictive performance by 36%. Therefore, BTS has been adopted by this study given the widely-reported successful applications in the literature.

Dishonest or careless answers can easily lead to inaccurate forecasts or unreliable research results. Weaver and Prelec (2013) pointed out that there are possibly three types of untruthfulness: intentional deception, inauthenticity, and carelessness. They also show that BTS effectively eliminates all three types of untruthfulness, and provide respondents with incentives to be truthful.

When a researcher knows the true answer to a question being asked they may reward truthfulness by rewarding participants for correct answers. However, in many situations the objective truth is unknown, for example we don’t know what the car-share market penetration will be in 2030. In such cases, one cannot use the real answer to incentivise respondents to give truthful answers.

The great innovation of the BTS scoring rule is that it does not require the researcher to know the objective truth in order to incentivize respondents. The model assumes that respondents are rational Bayesians who are willing to maximize their expected score, and incorporate expectation regarding others’ behaviours when giving their own response. The BTS uses the way information is typically distributed in the world, where respondents are Bayesians, who observe different signals and who are more or less informative about the true answer.

The BTS score consists of two components: an information score and a prediction score, as shown in Equation (1). The intuition behind the BTS scoring rule, particularly the information score, is that in a large sample of respondents with Bayesian beliefs, everyone expects their truthful answer to be the most “surprisingly common” answer, an answer that is more common than all experts collectively predicted. Therefore, the BTS gives higher information scores to participants whose answer is “surprisingly common” (i.e., more likely in the population than the respondent themselves would suspect); For example, if an answer was endorsed by 40% of the respondents but this answer is predicted to be chosen by only 5% of the population by respondents, then anyone who picked this answer would receive a high information score. The more truthful a respondent is, the more likely their answer is to be “surprisingly common” and therefore the more likely they are to get a high information score. Respondents are therefore incentivised to reveal their true beliefs to maximize their expected score. The second part or prediction score in Equation (1) assigns a higher score to participants who know how other experts think about a topic, thus those who predict the
empirical distribution of answers accurately will be rewarded with a higher score. The intuition behind this is that the informed experts would have access to meta-knowledge (or knowledge about knowledge), while novices do not.

As the researcher does not need to know the objective truth in order to apply the BTS scoring rule it is particularly useful for assessing the truthfulness of responses about unobservable outcomes, such as weather forecasts, business forecasts, energy price predictions, and the future market penetration of car-sharing.

In addition to incentivizing respondents to be honest and identifying more knowledgeable respondents, the BTS enables researchers to identify the likely truth when limited information is available (i.e., when the only evidence available is the private information of experts) provided that, by assumption, there exists one correct answer (truth).

It has been shown mathematically and experimentally in [Prelec and Seung, 2006] that the BTS effectively reveals the answer that is most likely to be true in a situation where the majority were wrong.

In terms of the sample size required for using BTS, it has been shown by [Weaver and Prelec, 2013] that BTS is robust (the truth telling incentive holds) towards different sample sizes and also performs well with small sample sizes. More specifically, [Weaver and Prelec, 2013] found that the BTS scores appear to be fairly stable as number of respondents increases from 10 to 36. Moreover, from a regression analysis, [Weaver and Prelec, 2013] found that the effect on coefficient is only -0.005 for each additional sample, and that BTS was effective with even 10 respondents (This is the minimum number they tested and does not suggest the minimum sample size should be greater than 10).

There are also existing studies that applied BTS with a small sample. [Weiss, 2009] applied BTS with 83 students in a State Capital survey, which asks respondents to identify the capital of U.S. states, and with 28 respondents in a Chess experiment, which asks respondents to predict the next move in a chess game. [Miller et al., 2014] applied BTS with 71 students in a design class, which treats BTS score as a measurement of design expertise and compared it with the class outcome.

In order to apply BTS in a survey setting, participants must be asked to supply not only their answers but also to estimate the distribution of answers offered by all other respondents. These two different answers are then used to compute the BTS score. For instance, respondents, which is denoted by \( i \in \{1, \ldots, n\} \), are answering a multiple choice question with alternatives indexed by \( k \in \{1, \ldots, m\} \). The personal BTS score \( s_i \) for respondent \( i \) is calculated as:

\[
s_i = m \sum_{k=1}^{m} x^i_k \log \frac{x^i_k}{\bar{x}_k} + n \sum_{k=1}^{m} \bar{x}_k \log \frac{\bar{y}_k}{\bar{x}_k} \tag{1}
\]

Where \( x^i_k \) is a binary variable representing respondents’ stated endorsement for this question, \( x^i_k = 1 \) given that individual \( i \) chose option \( k \) and \( x^i_k = 0 \) if individual \( i \) did not choose option \( k \). Also, \( \bar{y}_k \) denotes the estimated value of expert \( i \) for option \( k \), that is expert \( i \)'s predictions of how many other experts will select answer \( k \); \( \bar{x}_k \) in Equation (1) is the arithmetic mean of \( x^i_k \), whereas \( \bar{y}_k \) is the geometric of \( \bar{y}_k \). There are four steps to select the best answer (obtain the most likely forecasts) [Prelec and Seung, 2006; Prelec et al., 2013]:

a. Calculate the arithmetic mean of answers (i.e., \( \bar{x}_k \)) and the geometric mean of prediction (i.e., \( \bar{y}_k \)) offered by all \( m \) respondents:

\[
\bar{x}_k = \frac{1}{n} \sum_{i=1}^{n} x^i_k \tag{2}
\]

\[
\log \bar{y}_k = \frac{1}{n} \sum_{i=1}^{n} \log y^i_k \tag{3}
\]

b. Calculate the BTS score for each individual by adding information score and prediction score:

\[
s^i = m \sum_{k=1}^{m} x^i_k \log \frac{x^i_k}{\bar{x}_k} + n \sum_{k=1}^{m} \bar{x}_k \log \frac{\bar{y}_k}{\bar{x}_k} \tag{4}
\]

c. Calculate the average BTS score \( \bar{s}_k \) for each option \( k \in \{1, \ldots, m\} \) in a question:

\[
\bar{s}_k = \frac{1}{n \bar{x}_k} \sum_{k=1}^{m} x^i_k s^i \tag{5}
\]
d. The answer that maximize \( \hat{s}_k \) is the desired answer for this question.

3.4. Principal Component Analysis (PCA)

In order to investigate the impacts of energy price on car-sharing we considered four types of energy in this paper: crude oil, petrol, natural gas, and bio-diesel. PCA is therefore employed to form an energy price index in this study to address the multicollinearity issue and reduce the complexity of the regression analysis. PCA is an approach used to not only reduce the total number of variables but to also effectively describe multidimensional data with a small number of new variables. Suppose there are \( n \) variables: \( x_1, x_2, \ldots, x_n \). Then the linear combination of these variables is expressed as \( y = a_1 x_1 + a_2 x_2 + \cdots + a_n x_n \), where \( a_n \) are constants. The function, and the variance of the function, changes with the constants, and the first principal component is the linear combination that maximizes the possible variance. The second principal component is a linear function which is uncorrelated with the first principal component but also maximizes the possible variance, and so on for the third, fourth, and more principal components.

When applying PCA to a certain data set (Kaiser, 1960) suggests that the components with eigenvalues higher than one should be considered as principal components. With those selected principal components, approximately 75% of total variance is expected to be captured (Morrison, 1990). The details of the application and results of the PCA are presented in Section 5.

4. Analysis and Results

This section presents the main results of this study about the forecast of the future market penetration of car-sharing. More specifically, we generate forecasts for: (1) the future ownership mode, such as complete ownership and car-sharing; (2) the potential proportion of car-sharing use by different activities; and (3) the forecasted market penetration of car-sharing based on experts’ opinions (average-weighted or majority rule) and the forecasts weighted/aggregated based on the BTS score. We also study the impacts of participants’ expertise, energy prices, and vehicle purchase prices on experts’ predictions.

4.1. Car-sharing participation and vehicles ownership

Experts across all four countries were asked to provide their predictions for 2016 and 2030 in regard to the proportion of drivers owning a private vehicle or participating in car-sharing. As shown in Fig. 2a, experts indicated that the proportion of drivers who will own private vehicles in 2016 would remain relatively stable in Thailand and Australia (within +/- 2% of today’s numbers); however, an increase of 7-15% (3-6%) in new car ownership is anticipated in Indonesia (Malaysia). In terms of car-sharing in 2016, as seen in Fig. 2b, it appears that there will be no significant change (within +/- 2%) in the current proportion in all countries except in Australia, where an additional 3-6% of all drivers are predicted to participate in car-sharing programs by 2016.

Perhaps surprisingly, 29% of the experts expected the share of driver owning a vehicle in Malaysia to rise 16% or more within one year, which seems implausible as Malaysia already has one of the highest shares worldwide. Unrealistic answers in surveys are usually a result of respondents’ absence of interest (so those respondents give answers without careful thinking). To verify the existence of this issue in our survey, we checked the consistency of the answers given by these experts, and found that experts who predicted a high growth rate for 2016 also gave high growth rate for 2030. Such consistency implies that these answers are unlikely to be arbitrarily given.

If these answers are not caused by the respondents’ absence of interest, they are likely to be simply caused by the fact that these respondents were less informed experts, which is confirmed by our analysis. The average score for their answers is 0.597, suggesting that they honestly provided their answer. However, the average prediction score is very low, i.e., -0.827, suggesting they have less knowledge about car-sharing than other experts.

The proportion of drivers owning private vehicles in 2030 is predicted to be within 10% of today’s figures in Indonesia, Malaysia, and Australia; it is predicted that in Thailand the additional private vehicle owners by 2030 could be within 10% or increase by 11-25%, as these two forecasts were endorsed by an equal number of experts (Fig. 3a). Interestingly, the results also highlight the possibility of a reduction in drivers/owners by 2030, particularly in more-developed countries. This can be clearly seen in Fig. 3a, compared to forecasts for Thailand and Indonesia, where the distribution of experts’ predictions is concentrated over on the right-hand side, forecasts for Australia are distributed mainly over on the left-hand side. A total of 27% of experts expect to see a 51% or more decrease in

11
the proportion of drivers owning vehicles in Australia, also a significant proportion of experts in Malaysia (30%) expected to see the decreasing in vehicle ownership. Additionally, while the drivers’ car-sharing participation rate remains moderate (within +/- 10% compared to today) in Thailand and Indonesia in 2030, experts predict that by 2030 both Malaysia and Australia will have a significant uptake in car-sharing programs compared to the present, where 11-25% more Malay drivers and 26-50% more Australian drivers might become car-sharing members (Fig. 3b). This is in line with the possible reduction in vehicle ownership, suggesting that we will begin to see a shift from the current vehicle ownership culture to shared mobility services.

![Figure 2: Proportion of drivers participating in car-sharing OR owning vehicles in 2016](image)

**4.2. Car-sharing activities**

Furthermore, the detailed proportion for a range of activities or purpose of car-sharing use within four countries in 2016 and 2030 is summarized in Fig 4. The projected market share is based on the arithmetic mean of experts’ judgment in each country and the trip purposes were categorized as: commuting (work), holidays, shopping, education, visiting friends, and “other leisure” activities.

As shown in Fig. 4, Thai experts predict that car-sharing programs will predominantly be used for education, work, and holidays in 2016. This trend generally remains, as the proportions for work and education uses are expected to grow even bigger in 2030; however, the use of car-sharing in 2030 is anticipated to increase considerably for shopping, but decrease for holidays. Similarly, Indonesian experts predict that car-sharing programs will be particularly used for trips related to work and education in 2016 and increasingly popular in 2030. The market proportion of using car-sharing for holidays in 2016 is high, but is expected to decrease marginally by 2030. The market proportion for activities such as shopping, visiting, and other leisure are smaller, and this trend is likely to continue to 2030. In line with Thailand and Indonesia, Malaysian experts also predict that car-sharing programs will be used mainly for work, holidays, and education purposes in 2016. By comparison, market proportions for shopping, visiting, and other leisure are relatively small for both 2016 and 2030. In 2030, the market proportion for work, education, and shopping
are predicted to keep increasing, while the market proportion for holidays, visiting, and other leisure are expected to decrease.

In addition to work and shopping-related trips, Australian experts predict that car-sharing will also be used for activities such as visiting and other leisure. The use of car-sharing will continue to increase in 2030 for work, holidays, and education, although the market proportion for holidays and education will remain relatively low. The experts also predict that car-sharing will be less popular for shopping and other leisure in the future. In summary, the market proportions for car-sharing in Thailand, Indonesia, and Malaysia are expected to be very similar, where considerably large proportions are predicted for work, holidays, and education compared to all other activities. However, more recreational use of car-sharing programs is anticipated in Australia.

The predicted large but decreasing proportion of holiday trips in the three developing countries draws attention. Compared to Australia, where the proportion of holiday car-sharing use is predicted to increase from 2016 to 2030, the predicted drop in holiday-related car-sharing use in the three developing countries could be a result of the increased penetration of private vehicles. Given the relatively longer distances for holiday trips compared to other trip types, respondents are more likely to use private vehicles for holiday trips. As suggested by Wright and Fulton (2005), an increase in vehicle ownership will be triggered when income per capita reaches the range between US$2000 and US$5000. For instance China, which falls in this range, documented a 75% annual growth of vehicles ownership in 2004 (The Economist, 2005). A number of developing countries are approaching this income zone. The rise of private vehicles which occurred in China may be expected to take place in Thailand, Indonesia, and Malaysia in the future. In that context, the significant drop in proportion of holiday car-sharing can be seen as reasonable if there are no government regulations or guidance towards diversified mobility choices.
4.3. Forecasts of market penetration

The unweighted forecasts, which are based solely on experts’ opinions with the best answer being the one endorsed by most of the respondents (or average-weighted), and BTS-weighted forecasts of car-sharing market penetration are demonstrated in Fig. 5 and Fig. 6 respectively in terms of the proportion of all trips in 2016 and 2030 for the four countries.

Fig. 5a presents the unweighted forecasts of market potential for car-sharing programs in 2016. It shows that the majority of experts in Thailand, Indonesia, and Malaysia agreed that there will be no significant changes in car-sharing market penetration in 2016, thus a 0-2% increase in market penetration is predicted. The situation in Indonesia is a little different, as a 7-15% market growth is expected by the Indonesian experts. However, it is worth mentioning that 0-2% is endorsed by almost the same number of experts as 7-15%.

In addition to the unweighted answers, the BTS forecasts for the market in 2016 are summarized in Fig. 5b. The y-axis in Fig. 5b is the average BTS score for each category. There are five categories in total (x-axis). The BTS algorithm only ascribes a score to an answer which has been selected by at least one expert. If no experts choose a given answer it will not have a BTS score. Among the answers chosen by at least one expert, the BTS ascribes higher scores to ones which are more likely to be truthful. In Fig. 5b, taking Australia as example, the second category (i.e., 3-6%) receives the highest score and thus is believed to be the best prediction of market potential for Australia in 2016, whereas the third category (7-15%) is the second best prediction and so on. The missing values for the rest
of the three categories indicate that these answers have not been selected by any of the experts. Overall, the BTS are consistent with the unweighted forecasts for Thailand and Malaysia; however, according to the BTS, 0-2% and 3-6% are the most likely market penetration predictions for car-sharing in Indonesia and Australia in 2016, which is different from the majority rule. More specifically, the majority rule-based predictions overestimated the market penetration in Indonesia but underestimated the market penetration in Australia.

The unweighted forecasts indicate that the majority of experts predict that the market penetration in Thailand and Malaysia is most likely to be 11-25% in 2030 (Fig. 6a). For Indonesia, the unweighted one shows that the same number of experts endorsed 6-10% and 11-25%. The most selected answer for Australia is 6-10%.

Similarly, the unweighted answers are compared to the BTS (Fig. 6b). Based on BTS, the Thai and Malay car-sharing market penetration in 2030 could potentially grow to 11-25%. In addition, as the second best prediction, 25-50% receives almost the same score in Malaysia, indicating that the car-sharing market potential in Malaysia over the next 15 years could reach up to 50%.

As shown in Fig. 6b, according to the BTS, the market potential for car-sharing in Indonesia is most likely to be 11-25% in 2030. Also, car-sharing is predicted to be a predominate travel mode in Australia as of 2030, potentially holding up to half of the mobility market share (26-50%). This also suggests that the unweighted projections significantly underestimated the market penetration in 2030.

To sum up, the BTS suggest that car-sharing as a novel mobility service will not become prevalent (0-2% of the market potential) in 2016 in Thailand, Indonesia, and Malaysia. Its market potential in Australia is higher and can reach 7-15%. A significant growth in the car-sharing market in 2030 across all four countries is anticipated. More specifically, the market penetration in Thailand, Indonesia, and Malaysia is expected to reach 11-25%, and even as much as 26-50% in Malaysia. According to BTS, the car-sharing market potential in 2030 is very optimistic in Australia; that is, 26-50% as the most likely scenario and 11-25% as the second most likely scenario.

Figure 5: Forecasts of market potential forecasts in 2016
4.4. Investigating factors influencing experts’ beliefs about the future of car-sharing

In addition to the car-sharing predictions, we also investigated the factors that influence experts’ predictions. There are a range of factors affecting car-sharing behaviours, for example: street width, travel cost, travel time, access time, reliability, availability, etc. Different combinations of these variables have been considered by previous studies, and some promising results were found (as summarized in Table 1). However, it is obvious that there are too many factors to consider and many are context-specific, which makes the generalization of results difficult. An advantage of employing experts’ opinions is that experts’ predictions are based on taking all of these factors into account, through the prism of their own personal view on the topic.

In this study we consider two relative “macro” factors - energy price and vehicle purchase price, because these two factors are generally believed to be important to consumers when considering mobility choices. We elicited from our experts their predictions regarding future prices of common energy types, including crude oil, petrol, natural gas, and bio-diesel. However, there are strong correlations among these energy prices (see Table 5). In order to avoid potential multicollinearity issues, the principal component generated by PCA is used in our analysis as an energy price index that represents expert opinion regarding the overall trend of energy prices in the future.

Table 5: Pearson’s Correlation among variables for 2016/2030

<table>
<thead>
<tr>
<th></th>
<th>Crude</th>
<th>Petrol</th>
<th>LNG</th>
<th>Bio-diesel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Petrol</td>
<td>0.73/0.82</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LNG</td>
<td>0.61/0.75</td>
<td>0.49/0.76</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>Bio-diesel</td>
<td>0.56/0.67</td>
<td>0.68/0.64</td>
<td>0.68/0.84</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

The results of the PCA for the 2016 data indicate that the first component with an eigenvalue of 2.87 explains
72% of the total variance (Table 6), which is very close to the 75% threshold. Thus, we decided to only include the first component in order to control the complexity (number of dependent variables) in the regression analysis. The eigenvalue of the first component for the PCA using 2030 data is 3.24, and explains 81% of the total sample variance (Table 6). Again, only the first component is included for 2030 data.

Table 6: PCA of energy variables for 2016/2030

<table>
<thead>
<tr>
<th>Component</th>
<th>Eigenvalue</th>
<th>Cumulative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Component 1</td>
<td>2.87/3.24</td>
<td>0.72/0.81</td>
</tr>
<tr>
<td>Component 2</td>
<td>0.54/0.44</td>
<td>0.85/0.92</td>
</tr>
<tr>
<td>Component 3</td>
<td>0.41/0.18</td>
<td>0.96/0.97</td>
</tr>
<tr>
<td>Component 4</td>
<td>0.17/0.14</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

Meanwhile, experts were asked to predict the purchase price for nine vehicle types, including: Petrol vehicles, Diesel-powered vehicles, Liquid Petroleum Gas (LPG) vehicles, Hybrid electric-powered vehicles, Battery electric-powered vehicles, Fuel cell vehicles, Compressed Natural Gas (CNG) vehicles, Flexible fuel vehicles, and Biofuel vehicles. More specifically, experts were asked to identify the fuel types that will be prevalent in the future, and were then asked to predict the future purchase prices for each of these identified fuel types. The vehicle purchase price index is calculated by using the average of projected purchase prices for different vehicle types.

Results of the regression analysis are shown in Table 6. Surprisingly, neither future energy prices nor vehicle purchase prices were found to significantly influence experts’ predictions on car-sharing market development. This means that the supply-side experts believe that, when making car-sharing choices, customers are not sensitive to the change in fuel prices or the car purchase price, and experts do not expect customers to give up private vehicles solely because of the increasing cost of owning/driving a vehicle.

It has been shown previously that customers’ car use is not strongly discouraged by increasing fuel cost. For example, Kingham et al. (2001) conducted a survey in two companies (i.e., Mitsubishi and Matra BAe) in London, and found that a doubling of the fuel price only led to 12-20% of respondents stopping use of their private vehicles for work. Zheng et al. (2016) also confirm that consumers are not sensitive to the costs/disadvantages of the transport mode they frequently use, for example, owners of private vehicles tend to ignore the costs of driving a car but care more the costs/drawbacks of public transport that they do not use often. Compared to private vehicles where drivers have to pay for the fuel directly, fuel costs associated with car-sharing are indirectly applied to customers. Thus, an important question is: will those people who are willing to stop driving a private vehicle shift to car-sharing?

The insignificance of energy price in our regression analysis suggests that the increasing fuel price does not have a statistically significant impact on people’s adoption of car-sharing.

Intuitively, the vehicle purchase price should influence the evolution of the car-sharing industry. From results in this study it seems that experts do not form beliefs consistent with such an influence. However, this does not necessarily mean that vehicle purchase price is not important to consumers when they are making mobility choices. As mentioned above, the experts were also asked to predict the vehicle purchase price in 2016 and 2030. The majority of experts predict that the vehicle purchase price will most likely be “within +/− 2%” and “within +/− 10%” of current prices in 2016 and 2030 respectively. Therefore, such a small change in the predicted vehicle purchase price led the experts to consider vehicle purchase price as an insignificant factor when predicting the car-sharing market potential.

Moreover, as mentioned previously, it is easier for cities where car-sharing organizations have been operating already to reach a higher market penetration than those cities without any car-sharing organizations. As shown in Table 7, compared to Thailand, experts generally predict a higher market penetration for car-sharing in Indonesia, Malaysia, and Australia in both 2016 and 2030.

Additionally, since existing studies have already demonstrated that the BTS score is positively correlated with participants’ expertise (Miller et al., 2014; Weiss, 2009), the personal BTS score is employed as an index of expertise in this study. It is interesting to note that the higher the score, the lower the prediction for the market penetration.

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2http://www.mitsubishi-cars.co.uk/
3http://www.mhda-systems.com/
Table 7: Regression analysis of experts’ predictions on car-sharing market potential

<table>
<thead>
<tr>
<th></th>
<th>(1) Car-sharing in 2016</th>
<th>(2) Car-sharing in 2030</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thailand</td>
<td>Base case</td>
<td>Base case</td>
</tr>
<tr>
<td>Indonesia</td>
<td>0.920*** (4.07)</td>
<td>0.503* (1.72)</td>
</tr>
<tr>
<td>Malaysia</td>
<td>0.682*** (2.81)</td>
<td>1.006*** (3.59)</td>
</tr>
<tr>
<td>Australia</td>
<td>0.270 (1.01)</td>
<td>0.531** (2.13)</td>
</tr>
<tr>
<td>BTS expertise index</td>
<td>-0.782** (-2.02)</td>
<td>1.107*** (6.68)</td>
</tr>
<tr>
<td>Energy price index</td>
<td>0.0815 (1.13)</td>
<td>0.0390 (0.53)</td>
</tr>
<tr>
<td>Vehicle purchase price index</td>
<td>-0.0482 (-0.36)</td>
<td>-0.0866 (-0.83)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.507** (2.26)</td>
<td>2.317*** (4.27)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1) Answer for 2016</th>
<th>(2) Answer 2030</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thailand</td>
<td>0.117 (1.12)</td>
<td>0.408* (1.77)</td>
</tr>
<tr>
<td>Score for 2016</td>
<td>0.589 (1.58)</td>
<td>-0.0416 (-0.20)</td>
</tr>
<tr>
<td>Indonesia</td>
<td>0.928** (2.39)</td>
<td>1.006*** (3.59)</td>
</tr>
<tr>
<td>Malaysia</td>
<td>0.270 (1.01)</td>
<td>0.531** (2.13)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>70</td>
<td>72</td>
</tr>
<tr>
<td>R²</td>
<td>0.217</td>
<td>0.473</td>
</tr>
<tr>
<td>F</td>
<td>6.013</td>
<td>14.52</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

in 2016 in each country, meaning that the experts with more expertise (a higher BTS score) are relatively more pessimistic than the average respondent about the market expansion of car-sharing in 2016. An intuitive interpretation of this phenomenon is that the more-informed experts have more insightful knowledge of car-sharing, which helps them to more-accurately recognize the immediate challenges the industry will face to generate more demand in the short term and the future opportunities for expanding the market in the long term.

One concern for the regression analysis is that experts’ predictions for market potential in 2030 could be largely influenced by their prediction in 2016. Thus, the correlation between experts’ answers for 2030 and their answers for 2016 was tested. As summarized in Table 8, it is clear that experts’ answers for 2016 have no statistically significant relationship with their answers for 2030. In addition, there is a significant impact of the BTS score for 2016 on the BTS score for 2030, indicating that the more-informed experts who receive high BTS scores for their 2016 predictions also receive higher scores for their 2030 predictions. This is compatible with the higher BTS score capturing a greater level of expertise from the respondents. Furthermore, the fact that this subgroup of experts gave predictions different from the group average suggests that they intentionally did so, highlighting the trustworthiness of these responses.

Table 8: Regression analysis of experts’ predictions on car-sharing market potential

<table>
<thead>
<tr>
<th></th>
<th>(1) Answer for 2016</th>
<th>(2) Answer 2030</th>
</tr>
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<tbody>
<tr>
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<td>0.531** (2.13)</td>
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</tbody>
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<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>70</td>
<td>72</td>
</tr>
<tr>
<td>R²</td>
<td>0.096</td>
<td>0.059</td>
</tr>
<tr>
<td>F</td>
<td>1.806</td>
<td>1.016</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
4.5. Validity and reliability

Furthermore, due to the underdevelopment of car-sharing at present (particularly in developing countries) and considering the rapidly emerging trend towards sharing-based economies that we are witnessing, as well as the particularly strong need for alternative mobility services worldwide, it is natural for experts to give a prediction of low market potential for 2016 and a high one for 2030. Therefore, an easy way to further test the quality of the survey data (and thus the quality of our results) is to check if responses from each participant follow this trend. As shown in Fig. 7, the green line at the top part represents the sum of BTS score for two questions related to car-sharing penetration (recall that BTS is calculated question by question); the plots at middle part show individuals’ scores for two questions. Interestingly, the blue line is relatively more stable than the red line, suggesting that the diversified total score is largely contributed by the significant variance in scores for the 2030 question. This is understandable as long-term forecast involves more uncertainty. Furthermore, at the bottom part of Fig. 7, the red line is generally above blue line, the gap between experts’ predictions for 2016 and 2030 can be clearly identified. Among the total of 73 experts, only seven of them gave ambiguous predictions, because their predictions for 2016 and 2030 overlap, for example 3-6% for 2016 and 0-5% for 2030. However, this only suggests that they are relatively pessimistic toward the industry and think there will be no dramatic change in the industry over the next 15 years. Only one participant, which is the first respondent in Fig. 7, gave a highly atypical prediction (higher market penetration in 2016 than 2030). The BTS score enables us to effectively pick up this participant because he/she also received the lowest BTS score.

Figure 7: Comparison of experts stated market potential for 2016 and 2030

Comparing predict with real world data will allow us to validate our result directly. Unfortunately, there seems no
credible sources available or accessible yet. It is even the case in Australia, even though data availability/accessibility in Australia is the best among these four countries. There were three car-sharing operators in Australia in 2016: CoGet, Green Share Car, and Hertz 24/7. The results would be easily compared if data regarding trip or memberships from these companies were available. However, as stated in Kent and Dowling (2016), the exact figures on the members of these three companies are not publicly available. This is actually typical in the industry, for example, Uber was founded in 2009 but only released their trip data in 2017 (Bensinger, 2017). Therefore, in order to validate our approach, we also asked experts to predict the price change of energy (e.g., crude oil and natural gas), because energy and transport are closely related sectors, and the publicly traded oil and gas allow us to easily compare the predicted with the actual prices. As shown in Figure 8, the columns in black represent predictions of the crude oil prices in four countries provided by this study. Specifically, a range between US$41.37 and US$56.46 per barrel is predicted for the crude oil price in 2016. As shown by the orange column in the middle, the actual average crude oil price in 2016 is about US$43.33/barrel. The column in blue represents the forecast by the U.S. Energy Information Administration (EIA). EIA provides prediction for future crude oil price in their Annual Energy Outlook (AEO). According to EIA (2015), the crude oil price was projected to be US$71/barrel in 2016. The predictions by our study are clearly much closer to the actual crude oil price in 2016.

In addition, the red horizontal dashed line in Fig. 8 indicates the actual average crude oil price in 2015, which is US$48.67/barrel. As shown in Figure 8, the crude oil price dropped from US$48.67/barrel in 2015 to US$43.33/barrel in 2016. Based on our results, although the experts from Australia, Indonesia, and Malaysia predicted that the crude oil price would be marginally higher in 2016 than it was in 2015, the price drop was correctly predicted by the experts from Thailand. This again confirms the validity of our approach.

Figure 8: Comparison of the crude oil price forecasts (Zhou and Page, 2017)

https://www.hertz247.com/Australia/
5. Discussion and Conclusions

Many studies have investigated issues related to car-sharing demand modelling with different methods and various variables (factors) \cite{Prettenthaler2006, Schuster2005, Catalano2008}, and some promising results have been reported. This study takes a different approach by focusing on the opinions of the transport experts. More specifically, to cover the important elements related to car-sharing future demand as much as possible, and also to control for its complexity, this study adopted a newly-developed method for expert elicitation and aggregation (i.e., BTS). The main findings presented in this study are summarised below.

Car-sharing in Thailand, Indonesia, and Malaysia are generally used for activities related to work or education. Apart from commuting use, more recreational use such as shopping, visiting, and other leisure are anticipated in Australia. Moreover, there would be a significant drop in the proportion of holiday car-sharing use in developing countries, and we believe this is partly due to the expected increasing ownership of private vehicles.

The emergence of car-sharing programs, combined with the emergence of sharing-based economies (influenced significantly by applications such as Uber and AirBnB), has resulted in consumers being more open to alternatives to existing models. Based on our BTS forecasts, the car-sharing market penetration in 2016 is estimated to be around 0-2% in the Thai, Indonesian, and Malaysian mobility markets, and 3-6% in the Australian market with the possibility of reaching 7-15%. Compared to \cite{Shaheen2013}, which predicts a market potential of 4.2% in Asia and 3% in Australia between 2010 and 2015, our results suggest a lower market penetration in Asian countries but higher potential in Australia, however, such difference could be caused by different forecasting times, and the distinct forecasting areas (if other Asian countries like Japan and Korea were included in our study, the figure could be higher). The projected market potential for 2030 is 11-25% in Thailand, Indonesia, and Malaysia, and 26-50% in Australia, while the car-sharing market in Malaysia could also potentially reach 26-50%. To the best of our knowledge, there is no existing study providing forecasts of car-sharing potential towards 2030 for the Asia-Pacific market, thus no comparison could be drawn.

The BTS forecasts also show that the unweighted forecasts, which are based on the majority rule, could be misleading. For example, from the unweighted forecasts, the Indonesia market in 2016 is 7-15% while the Australian market in 2030 is 6-10%. These figures are not realistic, given the fact that the first two car-sharing programs (i.e., Trippes and Hipcar) in Indonesia were only introduced in late 2015 and covers only Jakarta and Bali. In contrast, a faster development in Australia compared to the other three developing countries should be anticipated, given that the current level of car-sharing exposure in a city influences the speed or time needed to reach the market potential \cite{Loose2006}. The market potential could be reached in the medium-term future in cities currently being serviced by car-sharing, whereas cities in which no car-sharing programs exist at present will need a longer time to reach the market goal \cite{Loose2006}. The car-sharing industry is relatively undeveloped in Thailand and Indonesia, whereas several well-known car-sharing providers already exist in Malaysia (COMOS, roadaz, etc.) and Australia (GoGet, Flexicar, etc.). In addition, car-sharing usually complements walking, cycling and public transport (PT). Thus, compared to small or underdeveloped cities, it is easier to establish car-sharing programs in developed cities where good infrastructure exists to support pedestrians, cyclists, and public transport users \cite{Katz2003}. Due to the novelty of this travel mode, its adoption process is likely to be slower in Thailand and Indonesia than in Australia and Malaysia. Therefore, the BTS forecasts of 0-2% for Indonesian market potential in 2016 and 26-50% for Australian market potential in 2030 are more realistic than the forecasts of 7-15% and 6-10% respectively by the majority rule (the unweighted forecasts).

Two main findings can be drawn from the regression analysis. First, from the supply-side perspective, expected energy prices and vehicle purchase prices do not have a statistically significant impact on experts’ belief on the adoption of car-sharing. The exogenous forecast provided by our experts can be treated as an aggregated consumer preferences, thus the question whether the changes in fuel price would facilitate the adoption of car-sharing is answered. Our analysis shows that experts across all four countries consider their effects as minimal. In addition, people intuitively believe that the change in vehicle purchase price will influence consumer preference towards car-sharing. This might be true; however, from our survey the purchase prices are expected to be quite stable during the next 15 years. If we had forced experts to predict the market potential of car-sharing in scenarios where vehicle purchase price increased

\footnotesize{http://www.flexicar.com.au/}
by a certain amount (50% for example), we might have observed a significant impact of vehicle purchase price on
car-sharing market potential. However, such a result cannot be applied to the reality due to its hypothetical nature.
Instead, we asked experts to predict vehicle purchase price in 2016 and 2030. Consequently, the purchase price is
predicted to be stable and has no significant impact on car-sharing evolution.

Second, the experts with BTS scores higher than the average tend to be more pessimistic about the car-sharing
market penetration in 2016 but more optimistic towards 2030. As shown in previous studies, the BTS score is posi-
tively correlated with respondents’ expertise. Thus we can conclude that those more-knowledgeable experts are more
insightful, by recognizing the immediate challenges the industry is facing and by being more aware of the future
opportunities. A focus-group study with the experts, especially the more-informed (higher BTS scores) group of ex-
erts, could be a useful follow-up study to investigate the resources, policy incentives, regulations, etc. the car-sharing
suppliers need in order to reach the projected market potential.

Based on these results, policy makers or stakeholders will need to take action in advance in order to prepare for
the upcoming changes. As the purpose of car share varies from country to country, car-sharing schemes/plans should
be specifically designed to attract different customers. For example, more flexible schemes should be introduced in
Australia, as customers are expected to share car for recreational purpose. Facilities like car share stations should
be set up at a wide variety of locations including national parks, beach side, high density urban areas, etc.; whereas,
car-sharing operators in Indonesia, Malaysia, and Thailand should focus on educational or CBD areas, as car-sharing
will be mainly used for work and school as forecasted.

While a shift towards car-sharing services can bring economic and environmental benefits, one obstacle for car-
sharing adoption is the low public awareness at present, especially in developing countries. As one of our Thai experts
stated that car ownership is seen as a symbol of status, adopting car-sharing and giving up ownership in Thailand can
be more difficult. Thus, effective educational programs is important for promoting car sharing services. Trial programs
that allow people to experience car-sharing services can also be helpful in increasing public awareness and acceptance.
Meanwhile, car-sharing is expected to work more efficiently if the public transport system is well developed. One
of our Indonesian experts commented that if public transport is not improved, private vehicle will still be the first
mode choice. Similarly, an Australian expert suggested that bundling car-sharing with public transport holistically
(e.g., having the same payment method) would facilitate car-sharing adoption.

Results of this study can be particularly useful for countries like Thailand and Indonesia where car-sharing organ-
isations do not exist or are underdeveloped at present. Compared to developed countries where vehicles per capita is
very high, indicating that car-sharing is essentially trying to get people out of private cars, car-sharing in developing
countries with a low car ownership works to fit more people into fewer cars, which is easier than getting people out of
private cars because as shown in Zheng et al. (2015) and Zheng et al. (2016). travellers are generally more sensitive
to the cost (or disadvantages) of the non-chosen transport mode and less sensitive to the cost (or disadvantages) of the
chosen mode even when experiencing large disruptions caused by natural disasters. This suggests that the popularity
of ride-sharing (carpooling) in Asian countries and the low ownership of private cars would facilitate the adoption or
promotion of car-sharing in this region.

As mentioned previously, there are many different methods for investigating the future uptake of new technologies.
To avoid some of the shortcomings suffered by many existing methods this study has employed expert elicitation and
aggregation. With the assistance of experts, we can avoid relying on consumers to forecast future preferences, which
could encounter many problems such as state dependence and high complexity. However, as with any approach,
this method has its own limitations. Some of the limitations are related to the method of expert elicitation and
aggregation in general, such as experts are not right about everything, and there is much about the future that is
inherently unknowable. Some of the limitations are more specific to our study, for example, the car-sharing industry
involves both suppliers and customers, thus the results of this paper that are based on the supply-side survey need to
be compared with the results of a consumer survey. We believe a more comprehensive picture of the future car-sharing
market can be drawn by comparing and analysing opinions from both experts and customers; such work is ongoing.

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