The role of social networks amongst early adopters of ride sharing schemes in the UK

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1. Introduction

An innovation is "an idea, practice, or object that is perceived as new by an individual or other unit of adoption" (Rogers, 2003). However, diffusion and adoption of innovation does not occur equally for every innovation in a social system: it is a social process where some people are more willing to accept an innovation than others. That is, some people are more receptive towards innovations and new ideas, and they perceive low risk in trying things that are new and novel (Rogers, 2003). Therefore, it is important to understand the characteristics of a target population when promoting an innovation. Rogers (2003) also identifies five key characteristics that determine diffusion. These are relative advantage, compatibility, complexity, trialability and observability. In order for information, which is the essence when it comes to the diffusion process, to be exchanged the communication channels, trialability and observability are very important. The trialability is the degree to which an innovation may be experimented with on a limited basis, and the observability is the degree to which an innovation is visible to others and therefore it has an impact on this social process.

One such innovation is the sharing economy. The concept of the sharing economy although broad can be described as "where people offer and share underutilized resources in creative, new ways" (Cohen & Kietzmann, 2014). One of the many segments of the sharing economy is – shared mobility. Car and ride sharing are examples of shared mobility. In contrast to public transport policy which is focused on "minimizing congestion" and people's desire to travel as less as possible, the sharing economy is focused on the "optimal congestion" (Lyons & Urry, 2005). This goal is possible to achieve through (1) modal shift, (2) fewer trips, (3) increased efficiency and (3) distance reduction. Modal shift involves replacing single occupancy vehicles with other forms of shared transportation. Fewer trips are related to a reduction of travelling in order to achieve some goal which can be accomplished through online shopping.

Transport efficiency is related to reduced impacts on the environment through more efficient use of public transport and therefore lower footprint vehicles (Banister, 2008).

Although the sharing economy is gaining more attention from researchers, there is a lack of research as to who early adopters of shared mobility are. Moreover, little is known about the role of social networks in influencing the growing interest in shared mobility. In this study, our research questions are *(1) What are the characteristics of early adopters?* and *(2) How connected are they through social networks?*

This paper uses data from the Understanding Society survey to test the hypotheses. This survey is conducted annually in the UK and captures information about people's social and economic circumstances, attitudes, health, attitudes, family situation and employment.

2. Theory

2.1 The socio-demographic and lifestyle characteristics of early adopters

This study draws on Rogers' (2003) theory of innovations and social network theory. In the theory of innovations Rogers (2003) distinguishes between five adopter groups: (1) innovators, (2) early adopters, (3) early majority, (3) late majority and (4) laggards. Only 16% of consumers are classified either as innovators or early adopters. These individuals are more attracted to novelty and have the greatest degree of opinion leadership in the social system. Rogers (2003) suggests that early adopters are highly educated, younger individuals with higher social status. In a survey of car club membership, Carplus (2016) finds that 60% of their members are below age 44 with 29% aged between 25-29. Early adopters also tend to live in urban areas (Rayle, Shaheen, Cervero, Chan, & Dai, 2014). Furthermore, they tend to be the opinion leaders, highly respected within their social system (Rogers, 2003). In this way, they exert the influence on the diffusion process.

Over the last 15 years, transportation patterns have changed. It is argued that there is a decrease in vehicle ownership per household with a corresponding increase in the use of public transportation (McKenzie, 2014). Compared to older generations, changes in travel patterns have occurred due to changes in the general lifestyle and behaviour of the younger people, commonly referred to as “Generation Y” or “Millennials” (Alemi, Berliner, & Tiedeman, 2016). They tend to marry later, postpone childbearing and also have fewer children than older generations (Alemi et al., 2016). This group is also considered dynamic and it is able to adjust more quickly to changes that occur (e.g. in an economy). Also, they are frequent users of ICT (information communication technology) devices and therefore, more willing to use possibilities that are offered by the sharing of mobility. In comparison to the older generation, millennials tend to postpone the time when they get their driving licence, frequently choosing to not own the car and live in the urban areas where public transport is available (Blumenberg, Taylor, & Smart, 2012; Kuhnimhof et al., 2012; McDonald, 2015; Puhe & Schippl, 2014).

The Carplus annual survey (2016) conducted among car club members in England and Wales (excluding London) shows that joining a car club leads to lower levels of car ownership. Also, even though some of users still own a private car, they tend to decrease usage significantly. Before joining the car club 38% of users drive by car at least once per week. After the joining this number reduces to 29%. Survey results also show that members often use public transport to commute and men are more likely to be members. The recent data for 2016 shows that 70% of car club members are males compared to 30% of females (Myers & Cairns, 2008). These findings lead us to test the following hypotheses:

H_1: *The more educated you are, the more likely you are using ride sharing services*.
H_2: *Early adopters are more likely to be employed.*
H_3: *Individuals with higher income are more likely to use ride sharing services than with lower income.*
H_4: *People who live in urban areas are more likely to use ride sharing services than people who live in rural area.*
H_5: *Early adopters are more likely to be men and travel by public transport.*

2.2. The social network characteristics of early adopters

Social networks consist of a series of interconnected nodes (individual actors, people, or things within the network) that characterize network structures (e.g. an idea related to ridesharing) (Borgatti, Mehra, Brass, & Labianca, 2009). Communication networks consists of interconnected individuals who are linked by pattern flows of information (Rogers, 2003). This network structure provides predictability to human behaviour. The most effective way of sharing an idea about an innovation is through communication channels. Rogers (2003) distinguishes between different channels of communication. Interpersonal communication consists of both face-to-face and mass media. These are most effective in terms of sharing information since they can reach large audiences (e.g. television, radio etc.). However, he also defines communications channel as "the means by which messages get from one individual to another ". Millennials are born and raised in the era of sophisticated technology and this has influenced their communication behaviour, social habits and mobility choices. We therefore also hypothesise:

H_6: *Early adopters are more likely to have frequent communication behaviour and be socially active.*

H_7: *Early adopters are more likely to be frequent users of communication technology.*

Interpersonal networks are most important in terms of sharing information about an innovation. Communication across these networks occurs in many ways including through social media, face-to-face, mass media etc. Early adopters are seen as opinion leaders and therefore their role is to help reduce uncertainty about innovation and thus to influence others across these networks. It is known that the behaviour of close personal networks has a strong influence on an individual's adoption behaviour (Valente, 2010). Since early adopters are well connected to others, communication flow is enhanced by homophily within their social network (Rogers, 2003). Homophily is a tendency that individuals with common or similar social characteristics and attributes associate with each other (Lozares, Miquel, & Irene, 2014). In terms of Granovetters' (1983) strength of week ties theory, the homophilous networks consists of strong ties (e.g. close friends) that are socially involved with each other. This arises because of structural availability rather than choice. Individuals with whom we come into contact are ones that we associate with often at work, within neighbourhoods and other places where we tend to be present (Brashears, 2015). Therefore, we also hypotheses:

H_8: *Early adopters are more likely to have strong local ties.*

H_9: *Early adopters are more likely to have homogeneous networks.*

H_{10}: *Early adopters are more likely to have large social networks compared to non-adopters.*

3. Methodology

This study uses data from Understanding Society, the UK Household Longitudinal Study which surveys approximately 40,000 households across the United Kingdom. This study is focused on the adult survey conducted between 2014-2016.

3.1 Data

Ride-sharing

The survey distinguishes membership in formal car-sharing programmes and car clubs. Due to the small sample size and overlap of variables for car sharing programmes and car clubs, we merged the samples and we refer to as dependent variable ridesharing *C4*. We create a dummy variable where 1 is car or rideshare and 0 is neither.

Demographics

The variables for gender, residential area, high education, dependent children at home and income were recoded as dummy variables for easier interpretation. The variable sex is recoded as *gender* (0=male, 1=female), and residential area as *urban* to distinguish whether people live in the urban or rural area. Previous studies have shown that early adopters are often highly educated and therefore we create dummy variable *edu* and we distinguish between people who have degree and others. Also, we thought that dependent children at home could have an impact on whether an individual is an early adopter or not and therefore we create dummy variable *depchild* to distinguish between people who have a child and does not. It is shown that early adopters often have a high income, for the annual income variable we create dummy variable *income* to distinguish between lower and higher income individuals. The variable *age* is used as a continuous variable from the dataset.

Lifestyle

The variables for car ownership and usage of car/van were recoded into *car* and *carusing* as dummy variables. Since early adopters are more likely to use public transport than others, we recoded variables for travel by bus and travel by train as categorical variables *bus* and *train* (daily/sometimes/never). Early adopters tend to be economically active, and therefore current economic activity variable was recoded as a categorical variable *job* (employed/unemployed/other). Also, a legal marital status variable was recoded as categorical variable *marital* (single/married/divorced). As early adopters tend to be frequent users of information communication technology, we recoded variables has a mobile phone, has a smartphone and has a mobile computing device as dummy variables *havingmob*, *havingsmart*, and *havingmobcomp* for easier interpretation. The variable for frequency using the internet was recoded into categorical variable *freqnet* (daily/sometimes/never).

Social Networks

The variables whether a person likes a present neighbourhood, belong to a social website and go out socially, we recoded into dummy variables *likesne*, *belongsocweb* and *goout.* The variables related to similarities with others related to age, race, education, income and job were recoded into categorical variables *similararea, similarage, similarace, similaredu* and *similarjob* (more than half/half/less than half). Additionally, we recoded variables proportion of friends who are also family members and proportion of friends living in a local area into categorical variables *similarfam* and *similararea* (more than half/half/less than half). Lastly, the variables whether the person feels that belong to the neighbourhood and whether plans to stay in the neighbourhood were recoded into categorical variables *belongneig* and *stayne* (agree/neither agree or disagree/disagree).

4. Analysis

For each group of the variables *Socio-demographic*, *Lifestyle* and *Social Networks* we run independent t-tests and where is necessary, we also run a Chi2 test. Only statistically significant variables were further included in the models and tested with logistic regression. All statistical analyses were done in Stata (version 14).

4.1 Descriptive statistics

Table 1. Ride sharing and socio-demographic variables

Variables		

Ride sharing	yes no	355 (0.95%) 36,984 (99.05%)
Gender	female male	24,316 (53.69%) 20,972 (46.31%)
Age	range mean	16-102 47
Education	degree others	15,811 (36.39%) 27,640 (63.61%)
Income	high low	12,927 (28.57%) 32,326 (71.43%)
Urban area	urban rural	35,081 (77.47%) 10,202 (22.53%)
Dependent children at home	yes no	13,297 (34.18%) 25,603 (65.82%)

As Table 1 shows, less than 1 % of the UK population use ride sharing schemes. This places it within the early adopter stage of diffusion where only 16 % of people adopt an innovation. Rogers' (2003) assume that early adopters have more years of education which is the opposite of what it is observable from the table where 63.6 % of people does not hold a degree. Also, it is assumed that early adopters have higher social status but we can see that the majority of people reported that they have low income.

4.2 Hypotheses testing

Table 2. T-test results for socio-demographic

Variable	Hypotheses	t-value	df	p-value
Gender	H_5: *Early adopters are more likely to be men and travel by public transport.*	3.5458	37336	0.0004*
Age	/	3.4298	37337	0.0006*
Income	H_3: *Individuals with higher income are more likely to use ride sharing services than with lower*	-6.2934	37307	0.0000*

	income.			
Education	H_1: *The more educated you are, the more likely you are using ride sharing services.*	3.8794	37240	0.0001*
Urban/rural	H_4: *People who live in urban areas are more likely to use ride sharing services than people who lives in rural area.*	1.1714	37330	0.2415

* = significant at 0.05 level

The t-test results indicate that the difference of means in ride sharing and in terms of gender, income, age and education were statistically significantly different from 0. Whereas the difference of means in ride sharing and living in urban area, were not statistically significantly different from 0.

Table 3. T-test results for lifestyle variables

Variable	Hypotheses	t-value	df	p-value
Car ownership	/	-1.4373	37322	0.1507
Using car/van	/	0.2385	28725	0.8115
Dependent children	/	-1.0197	31587	0.3079
Has mobile phone	H_7: *Early adopters are more likely to be frequent users of communication technology.*	2.1414	37332	0.0322*
Has smart phone		4.0190	35106	0.0001*
Has a mobile computing device		3.3570	37332	0.0008*

* = significant at the level 0.05

The t-test results indicate that the difference of means in ride sharing and in terms of having a mobile phone, smart phone, and a mobile computing device were statistically significantly different from 0. Whereas the difference of means in ride sharing and being owner or user of a car and having dependent children at home were not statistically significantly different from 0.

Table 3.1 Chi2 test results for lifestyle variables

Variable		**Chi2**	**df**	**p-value**
Travel by bus	H_5: *Early adopters are more likely to be men and travel by public transport.*	7.5121	2	0.023*
Travel by train	H_5: *Early adopters are more likely to be men and travel by public transport.*	7.0944	2	0.029*
Marital status	/	4.6012	2	0.100
Frequency using internet	H_7: *Early adopters are more likely to be frequent users of communication technology.*	22.0021	2	0.000*
Job (current economic activity)	H_2: *Early adopters are more likely to be employed.*	57.4860	2	0.000*

* = significant at the level 0.05

The Chi2 results indicate that there is statistically significant relationship between the ride sharing and using public transport (bus and train), frequency using the internet and being employed. In contrast, there is no statistically significant relationship between ride sharing and being legally married.

Table 4. T-test results for social network variables

Variable		**t-value**	**df**	**p-value**

Belong to social website	H_6: *Early adopters are more likely to have frequent communication behaviour and be socially active.*	3.9384	37324	0.0001*
Go out socially		1.3216	37293	0.1863
Likes present neighbourhood	H_8: *Early adopters are more likely to have strong local ties.*	-0.9922	37123	0.3211

* = significant at the level 0.05 level

The t-test results indicate that the difference of means in ride sharing and belonging to a social website were statistically significantly different from 0. Whereas the difference of means in ride sharing and going out socially and liking present neighbourhood were not statistically significantly different from 0.

Table 4.1 Chi2 test results for social network variables

Variable	**Hypotheses**	**Chi2**	**df**	**p-value**
Proportion of friends living in a local area	H_8: *Early adopters are more likely to have strong local ties.*	8.9749	4	0.062
Proportion of friends who are also family members		10.1974	4	0.037*
Close friends	H_{10}: *Early adopters are more likely to have large social networks compared to non-adopters.*	39.2234	42	0.594
Hours spent interacting with friends through social website	H_6: *Early adopters are more likely to have frequent communication behaviour and be socially active.*	4.4635	4	0.347
Belong to neighbourhood	H_8: *Early adopters are more likely to have strong local ties.*	2.9411	2	0.230
Plan to stay in neighbourhood		2.6949	2	0.260
Similar age		3.7826	4	0.436

Similar race	H_9: *Early adopters are more likely to have homogeneous networks*	5.6489	3	0.130
Similar education		10.6629	3	0.014*
Similar job		32.1941	3	0.000*
Similar income		2.4307	3	0.488

* = significant at the 0.05 level

The Chi2 results indicate that there is statistically significant relationship between the ride sharing and having friends who are also family members, having similar education and job. In contrast, there is no statistically significant relationship between ride sharing and having friends living in similar area, having close friends, how much hours someone spend interacting through social website, feeling to belong to neighbourhood and plan to stay in neighbourhood. Also, there were not statistically significant relationship between ride sharing and being similar with age, race or income.

In summary, from demographics group of the variables, the ones that were statistically significant in predicting ridesharing membership were gender, age, income and education. From lifestyle group of the variables, statistically significant ones were having a smartphone, having s mobile phone, having a mobile computing device, travel by bus, travel by train, frequency using the internet and being employed. From the social network group of the variables, the significant ones were belonging to social website, the proportion of friends who are also family members, having a similar job and similar education as your friends.

4.3 Logistic regression

As the dependent variable ridesharing (*C4*) is a binary variable, logistic regression was used. We used only statistically significant variables that we determined using t-test and Chi2 test with exception of having a mobile phone variable. We excluded this variable due to collinearity with the variable having a smart phone. In Model 1 we included only socio-demographic variables, in Model 2 we included demographics and lifestyle variables and in Model 3 we added social network variables.

Table 5. Logistic regression results

Model	Variables	Coefficient	p-value	Pseudo R2
1	Female	-0.289 (0.109)	0.008*	0.0146
	Age	-0.010 (0.003)	0.001*	
	Income	0.524 (0.117)	0.000*	
	Education (0 = degree)	-0.234 (0.114)	0.041*	
	_cons	-3.773 (0.249)	0.000	
2	Female	-0.272 (0.112)	0.016*	0.0199
	Age	-0.002 (0.004)	0.698	
	Income	0.307 (0.137)	0.016*	
	Education (0 = degree)	-0.157 (0.128)	0.214	
	Travel by bus	0.010 (0.110)	0.916	
	Travel by train	-0.048 (0.110)	0.730	
	Has smart phone	-0.123 (0.176)	0.457	
	Has mob. computing device	-0.102 (0.125)	0.390	
	Frequency using internet	-0.198 (0.123)	0.424	
	Job status	-0.296 (0.087)	0.000*	
	_cons	-3.404 (0.418	0.000	
3	Female	-0.304 (0.116)	0.009*	0.0230
	Age	0.000 (0.005)	0.941	
	Income	0.298 (0.130)	0.022*	
	Education (0 = degree)	-0.208 (0.122)	0.088	
	Travel by bus	0.000 (0.099)	0.997	
	Travel by train	-0.061 (0.112)	0.581	
	Has smart phone	-0.123 (0.173)	0.475	
	Has mob. computing device	-0.033 (0.122)	0.782	
	Frequency using internet	-0.105 (0.132)	0.427	
	Job status	-0.302 (0.098)	0.001*	
	Similar education	-0.153 (0.063)	0.015*	
	Similar job	-0.025 (0.068)	0.711	
	Family memb. who are	-0.108 (0.055)	0.048*	
	friends	-0.117 (0.142)	0.406	
	Belong to soc web.	-2.415 (0.520)	0.000	
	_cons			

* = significant at the level 0.05

Our results indicate that when we consider only (1) socio-demographic variables in Model 1, it accounts for 1,46 % of the variance in ridesharing adoption. The (2) lifestyle variables were added in Model 2 and this increased the variance to 1,99%. After adding (3) social network variables in Model 3, the variance increased to 2,30 %. We can conclude that the added lifestyle and social networks variables do account for more of the behaviour of early adopters regarding ride sharing.

Table 5.1 Average marginal effects on ride sharing (Model 3)

Model	Variables	dy/dx	z	p>|z|
3	Female	-0.00398 (0.001)	-2.60	0.009*
	Age	-0.00000 (0.00004)	0.07	0.943
	Income	0.00391 (0.001)	2.27	0.023*
	Education (0 = degree)	-0.00203 (0.002)	-1.70	0.090
	Travel by bus	-0.00000 (0.0010)	0.00	0.997
	Travel by train	-0.00060 (0.001)	-0.55	0.581
	Has smart phone	-0.00120 (0.001)	-0.87	0.385
	Has mob. computing device	-0.00003 (0.001)	-0.28	0.782
	Frequency using internet	-0.001 (0.001)	-0.79	0.427
	Job status	-0.00397 (0.001)	-3.34	0.001*
	Similar education	-0.00150 (0.001)	-2.42	0.016*
	Similar job	-0.00025 (0.001)	-0.37	0.711
	Family members who are friends	-0.00116 (0.001)	-1.97	0.049*
	Belong to soc web.	-0.00115 (0.002)	-0.83	0.407

* = significant at the level 0.05

For easier and more meaningful interpretation of the results, we used average marginal effects on ride sharing dependent variable for Model 3. Therefore, we can say that woman are 0.39% less likely to use ride sharing than men (Wald's z = -2.60, p>0.009). Having higher income increases the probability of using ride sharing services by 0.39 % (Wald's z = 2.27, p>0.023). Similarly, people who are unemployed are 0.39% less likely to use ride sharing than people who are employed (Wald's z = -3.34, p> 0.001). People who are connected to more heterogeneous social networks are 0.15% less likely to use ride sharing (Wald's z = -2.42, p>0.016). People who do not have strong ties to their family members are 0.10% less likely to use ride sharing (Wald's z = -1.97, p>0.049).

In comparing the effect of (1) socio-demographics, (2) lifestyle and (3) social network behaviour, the largest effect on whether or not people use ridesharing services is a lifestyle factor – being unemployed.

5. Discussion

The focus of this study is to examine who are early adopters and how connected they are through social networks. Using logistic regression, we tested and compared three models, (1) with socio-demographic variables, (2) addition of lifestyle variables and (3) with the addition of social networks variables.

As expected, the empirical results of this study indicate that early adopters of ridesharing services tend to be males which is in line with previous studies. We also find the support that people who tend to use ridesharing services have higher income, which is different than proposed in the previous studies. In terms of the lifestyle group of the variables, the most important one to predict whether someone will use ridesharing services or not is being unemployed. People who are unemployed are less likely to be users of ridesharing services. This is in line with Rogers' (2003) diffusion of innovation theory where he argues that early adopters have higher social status. However, previous research shown that early adopters are most likely unemployed because they tend to be full-time students (Alemi et al., 2016).

Even though previous research has shown that early adopters tend to be young people, we did not find the significance of the age when adding lifestyle and social network variables. This may be due to the variation of early adopter groups between different types of innovation.

In line with previous research, males are more likely to be users of ridesharing services. We found that 53,8 % of males are users. This could be because of the feeling of safety in general where females tend to be more careful when it comes to sharing a ride with strangers.

This can also be the reason why the older population is not willing to participate in activities related with interactions to strangers when it comes to adoption of innovation.

In terms of social networks, we found that people who tend to be users of ridesharing service indeed have homogeneous networks which is in line with the theory of innovation where it is assumed that people tend to be in contact with similar people to them in terms of education, race, age etc. A further implication of adding social network variables is that social networks nowadays indeed have a major role when it comes to adoption. Our study indicates that among socio-demographic predictors, addition of the lifestyle variables does increase predictability when it comes to be a user of ridesharing services. In addition, social network variables increase the predictability the most.

It is observable that ridesharing adoption in the UK is still just under 1 % of the population, therefore, it is still in its early stage of the adoption. However, sharing economy and specifically, ridesharing is still not researched enough and we are optimistic that there is still room for more people to embrace this practice.

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