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Adoption of ride-sharing apps by Chinese taxi drivers and its implication for the equality and wellbeing in the sharing economy

Xinchuan Liu

Weiai Xu

The Adoption of Ride-Sharing Apps by Chinese Taxi Drivers and Its Implications for Equality and Wellbeing in the Sharing Economy

Xinchuan Liu[a] and Weiai Wayne Xu[b*]
[a]*School of Journalism and Communication, Peking University, China;* [b]*N334 Integrative Learning Center, Department of Communication, University of Massachusetts Amherst, USA*

The adoption of ride-sharing apps is critical to the survival of taxi drivers in the mobile-driven sharing economy. Based on survey data collected from 1,195 licensed taxi drivers in Beijing, the authors present an integrated technology adoption model that combines technology and use factors (perceived usefulness and ease of use), social factors (word-of-mouth, peer adoption and subjective norms), system factors (socioeconomic and digital inequality), and audience factors (demographic characteristics and innovative personality traits). The results showed that adoption was innate, inherited, and socially driven. Adoption was positively associated with income, access to technologies, innovative personality trait, peer adoption, word-of-mouth, and perceived usefulness of the apps. The implications of the findings for inequality in the sharing economy are discussed.

Keywords: sharing economy; ride-sharing; ride-hailing; technology acceptance model; technology adoption; digital divide

Ride-sharing apps are one of many mobile innovations that have been introduced in recent years. These apps have changed the traditional taxi business by connecting riders directly with anyone who can provide transportation. Led by Uber, which had operations in 53 countries and more than 200 cities at the time of the study, the use of these apps has grown exponentially. In China, two domestic app-based services, Didi Dache and Kuaidi Dache, amassed 150 million users (Russell, 2015). However, this mobile technological innovation has led to social tension: traditional taxi drivers are being forced out by under-regulated and unlicensed freelance drivers (Harding, Kandlikar, & Gulati, 2016), which has resulted in protests in several cities (Huang, 2017).

The protests indicate how the wellbeing of traditional labor can be affected by a single innovation. The innovation represents an emerging phenomenon that is fueled by the diffusion of mobile applications in peer-to-peer sharing, which has created the new economic model of the *sharing economy* (Belk, 2014). In 2014, the sharing economy generated $14 billion in revenue, and it was expected to grow exponentially to $335 billion by 2025 (Yaraghi & Ravi, 2017). Many taxi drivers in China have rushed to join ride-sharing services to stay in business. In the US, city officials encouraged taxi drivers to use an Uber-style app (Fleeman, 2015). The wellbeing of traditional labor forces, such as licensed taxi drivers, depends on their participation in the sharing economy. However, similar to any disruptive technology, the mobile technologies that are essential to the sharing economy have adoption thresholds that could replicate or reinforce the existing social inequality.

This study focuses on the issue of inequality in the context of how the adoption of ride-sharing apps is linked to various innate and structurally inherited factors. The study draws upon

*Corresponding author. Email: weiaixu@umass.edu

the latest integrated technology adoption model (Atkin, Hunt, & Lin, 2015; Lin, 2003) to test four factors: technological attributes, social influence, systematic inequality, and audience characteristics. The study seeks to answer the following question: *To what extent is technology adoption an outcome of the disparity in socioeconomic status, digital access and skills, personality differences, and social influence?*

To address these questions, this article is organized as follows. We first define the sharing economy and discuss its implications for equality. Next, we review the technology adoption model, which was derived from the literature and adapted to suit our focus on inequality. Finally, we test our hypotheses based on the synthesis of the predictors drawn from the model.

Inequality and Wellbeing in the Sharing Economy

The sharing economy has double-edged implications for the wellbeing of society. It empowers labor markets by encouraging freelancers to compete with formally organized and regulated labor by setting affordable rates and flexible terms (Codagnone & Martens, 2016). New entrants into the market benefit from the low entry barrier, flexibility, and operational efficiency (Yaraghi & Ravi, 2017). However, the origin of the sharing economy is in economic inequality; the global middle class uses apps such as Uber and Airbnb to generate extra income because of the pressure of unemployment and underemployment after the economic recession from 2007 to 2011 (Mirani, 2014; van Doorn, 2017). Because this market has little regulation or employment protection, freelance labor in the sharing economy is likely to face exploitation (van Doorn, 2017; Schor, 2017).

Our study contributes to the discussion on the societal implications of the sharing economy by focusing on the adoption of technology by traditional workers that are at risk of displacement. Our focus is based on two considerations. First, traditional workers are among the vulnerable and disadvantaged social groups. In China, taxi drivers are already at the lower end of the social strata, having few opportunities for upward social mobility because of their limited education and time for skill development (Nielsen, Paritski, & Smyth, 2010). Because of the rapid increase in private car ownership and traffic congestions in major cities, they have struggled to maintain their business. However, the question of how the traditional workforce fares in the sharing economy has been absent from the scholarly discussion. Second, the current literature mentions only briefly how the sharing economy reflects and reproduces the existing social inequality (see Schor, 2017). Moreover, no explicit link has been made between inequality and the cluster of factors related to technology adoption. In this article, we argue that technology adoption is not a matter of consumer preference but of livelihood for the traditional workforce. Thus, we must examine how inequality is manifest in the process of technology adoption.

The Integrated Technology Adoption Paradigm

The adoption of ride-sharing apps can be studied from multiple theoretical angles. On the macro level, adoption has been discussed as the diffusion of the innovation paradigm (Rogers, 2003). This paradigm explains why and how innovative ideas, practices, and techniques are accepted or rejected in a social system. Rogers (2003) considered diffusion a staged process, showing that innovators and early adopters were younger, more affluent, more knowledgeable, and socially connected than the general population. This paradigm, however, does not include micro-level factors (Atkin, Hunt, & Lin, 2015). Thus, several technology acceptance models were developed to incorporate individual factors (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003). Such models are used to explain how users evaluate the benefits and gains of adoption and how they are contingent upon social influence. The most recent adoption studies follow the integrated technology adoption paradigm (ITAP) proposed by Atkin, Hunt, and Lin (2015) and Lin (2003). This paradigm incorporates macro systemic factors as well as micro-level variables. The ITAP includes the following factors: *technology*, *use*, *social influence*, *system*, *audience,* and *adoption.* In the following sections, we discuss the salience of each factor in the context of ride-sharing apps, paying attention to the factors of system and audience.

Technology and Use Factors

In the ITAP, the term technology factors refers to the technical attributes of an innovation. A set of technical attributes was noted by Rogers (2003), which included trialability, complexity, relative advantage, compatibility, and observability. Technical attributes are also perceived subjectively, which leads potential adopters to have specific expectations of the technology (Lin, 2003). Early adoption models, such as the technology acceptance model (Davis, 1989) and the unified theory of acceptance and use of technology model (Venkatesh et al., 2003), consider two factors: *perceived usefulness*, which refers to perceived gains from an adoption, and *perceived ease of use,* which is “the degree to which a person believes that using a particular system would be free of effort” (Davis, 1989, p. 320). Prior studies showed that a significant role is played by the two factors in the use of mobile services (Deng, 2013; Kim, Chang, Wong & Park, 2015; Lin & Liu, 2009; Yuan et. al., 2016), social media (Suksa-ngiam & Chaiyasoonthorn, 2015), and electronic public services (Wang & Lo, 2013).

These two factors partially overlap the use factors in the ITAP. Both reflect the uses and gratifications of technology adoption. That is, people use technologies to fulfill various needs. Moreover, adoption and continuous usage are more likely to occur when the fulfilled gratifications outweigh the cost of adoption (Lin, 2003). Perceived usefulness reflects not only technical attributes but also how a specific array of technological, economic, and social needs can be satisfied by adoption. Regarding communication technologies in general, users are primarily concerned with the technological benefit of simulating a “social presence” in developing relationships or completing tasks (Lin, 2003). However, regarding ride-sharing apps, the gains are mostly in the economic realm, such as the ability to attract new customers conveniently as well as the potential sign-up bonus for first-time drivers. Adopting ride-sharing apps may lead to social gains. By adopting this app, taxi drivers show their sensitivity to and sophistication in using a new technology. The technical attribute of ease of use is associated with the cost of adoption. It is based on the notion of self-efficacy and the assumption that motivation increases when the individual is confident in using an innovation. Mobile apps are designed to be easy and intuitive. However, any adoption has technical barriers. If the app’s interface and configuration are cumbersome, then users may be discouraged from adopting it. Therefore, the following hypotheses are stated:

H1a: The adoption of ride-sharing apps is positively related to the perceived usefulness of ride-sharing apps.

H1b: The adoption of ride-sharing apps is positively related to the perceived ease of use of ride-sharing apps.

Social Factors

Socialization shapes adoption. Opinion leaders traditionally play a crucial role in disseminating mass media messages (Lazarsfeld, Berelson, & Gaudet, 1944). In the current digital era, social influence is derived from multiple channels, such as the mass media and traditional opinion leaders. Potential adopters, for instance, turn to their social circle for information and recommendations (Venkatesh et al., 2003). Interpersonal social ties exert different kinds of social influence. Weak social ties providing diverse information and innovative thinking, and strong social ties affect real and bonding behaviors (Weenig & Midden, 1991). Specifically, three sources of social influence are noted in the literature: word-of-mouth, peer adoption, and subjective norms.

Word-of-mouth is the influence of the cascade of information derived through interpersonal ties. In particular, personal recommendations are influential because they are more tailored and organic than promotional messages from organizational sources (Sun, Youn, Wu, & Kuntarapor, 2006). For example, the immediate social circle of taxi drivers includes the colleagues, friends, family, and customers with whom they interact daily. These people can provide personalized accounts of using ride-sharing apps, which sparks drivers' interest and alleviates their concerns about the technology. Previous studies showed that word-of-mouth is a key driver of the adoption and continuous use of various internet and mobile services (Kim & Son, 2009; Oh, Baek, & Ahn, 2015). Peer influence is a factor because peers face similar circumstances in the adoption of technology, and their commonality can reduce their uncertainty regarding the adoption of a technology (Atkin, Hunt, & Lin, 2015). The factor of subjective norms is a construct that was derived from the theory of reasoned action. The theory posits that people behave in ways that are approved or desired by others (Ajzen, 1991). Therefore, people make an adoption decision based on presumed social expectations (Venkatesh et al., 2003). Previous findings showed that the adoption of instant messaging tools and social networking sites was contingent upon subjective norms (Suksa-ngiam & Chaiyasoonthorn, 2015) and whether the surveyed participants' friends were current users of these technologies (Lin & Bhattacherjee, 2008). Therefore, the following hypotheses are stated:

H2a: The adoption of ride-sharing apps is positively related to the exposure to word-of-mouth.
H2b: The adoption of ride-sharing apps is positively related to peer adoption.
H2c: The adoption of ride-sharing apps is positively related to subjective norms.

System Factors

Technology adoption occurs in an open and evolving system that is marked by a unique hierarchy (Lin, 2003). System factors are macro-level structural, social, and behavioral forces that inhibit or facilitate technology adoption. They include several factors, such as telecommunication regulations, industry trends, market competition, and technology culture (Atkin, Hunt, & Lin, 2015). The internet censorship implemented by government regulators, for instance, creates the need to adopt censorship tools. Such needs are exacerbated by the adopters' political distrust of censors (Mou, Wu, & Atkin, 2016). Regarding ride-sharing apps, a salient system factor is how government regulators and technology developers balance the risks and opportunities arising from this new technology. The attitude of Chinese authorities toward ride-sharing was ambivalent at the time of the study. On one hand, the steady growth in the number of domestic apps (notably, Didi Dache), which replaced foreign competitors (i.e., Uber) and expanded globally, was a showcase for the government to promote the country as a leader in technology (Hong, 2017). On the other hand, protests by taxi drivers forced some local governments to consider restricting the apps (Waldmeir, 2015). Nevertheless, the overall regulatory and business environment was conducive to the adoption because the app's user base had been growing, compelling taxi drivers to capitalize on the new market. Moreover, several different apps competed to lure drivers to their platforms by offering subsidies and sign-up bonuses (Chen, 2015).

Regulations and business incentives have similarly affected drivers operating in the same market. It is unlikely that this system factor would result in variations in individual adoption. Thus, this study focuses on another set of system factors, which we summarize under the umbrella term, *digital divide.* The digital divide is a structural inequality in a communication system, which is manifest in the uneven access to technologies and technical knowledge (Hargittai, 2002, 2008, 2010). The effect of the digital divide on technology adoption is two-fold. First, the digital divide is concerned with the lack of access to devices and infrastructure, which is a salient problem not only in developing countries (Jimenez, 2016; Srinuan, Srinuan, & Bohlin, 2012) but also in developed economies (Mascheroni & Ólafsson, 2016). In China, the internet penetration rates reached 45.8% in 2014, and 81% of users had mobile access (CNNIC, 2014). These statistics indicate that a sizable portion of the Chinese population was left behind in the digital revolution, including some taxi drivers. Second, the digital divide limits the potential of the sharing economy. The lack of access to mobile technology prevents a signification portion of the Chinese population from participation. Moreover, the lack of access stems from the existing socioeconomic inequality in China (Leung & Wei, 1999, Livingstone & Helsper, 2007; Park, 2015, Wei, 2001). The existing disadvantages of those lacking economic resources could prevent them from participating in the sharing economy. In short, technology adoption is associated with the existing access to technological tools, and socioeconomic factors affect the general access to technologies and the ability to make decisions regarding their adoption. Therefore, the following hypotheses are stated:

H3a: The adoption of ride-sharing apps is positively related to drivers' socioeconomic status.

H3b: The adoption of ride-sharing apps is positively related to drivers' existing access to technologies.

H3c: Drivers' current access to technologies is associated with their socioeconomic status.

The second level of the digital divide concerns the lack of *digital literacy* (Hargittai, 2002). Having devices and access to the internet does not equate to putting technologies to their best use. Users with high digital literacy benefit from using a new technology. Previous studies showed that higher digital literacy was linked to better outcomes in e-commerce (Bhatnagar & Ghose, 2004), e-learning (Mohammadyari & Singh, 2015), job-seeking (Fountain, 2005), support-seeking (Van Deursen & Van Dijk, 2014), socialization (Valkenburg & Peter, 2007), and civic participation (Campbell & Kwak, 2010). Particularly relevant to the current context is the finding that high digital literacy was a predictor of early technological adoption (Hargittai & Litt, 2012; Mbatha, Ocholla, & Roux 2011). Moreover, digital literacy was found to be dependent on existing socioeconomic inequality: higher socioeconomic status was associated with the increased and better use of new technologies (van Deursen & Van Dijk, 2014; Park, 2015). For this reason, if taxi drivers lack digital literacy, it could become a barrier to their adoption of a technology. Thus, the lack of digital literacy inhibits the potential of the sharing economy to promote social mobility. In this study, we explore the second level of the digital divide and the existing socioeconomic inequality. Therefore, the following hypotheses are stated:

H3d: The adoption of ride-sharing apps is positively related to drivers' digital literacy.
H3e: Drivers' digital literacy is associated with their socioeconomic status.

Audience Factors

Audience factors are a group of influences on technology adoption. The original adoption model in ITAP highlights three audience-related factors: social locators, personality traits, and motivation (Atkin, Hunt, & Lin, 2015). Our model incorporates social locators and personality traits. Regarding social locators, notable gender differences were reported in the adoption of and activities on cellphones (Leung & Wei, 2000), social networking sites (Hunt, Atkin, & Krishnan, 2012), and the use of censorship circumvention tools (Mou, Wu, & Atkin, 2016). It was found that males were more receptive than females to technology adoption (Rogers, 2003). Technology adoption is also associated with age. Older people tend to seek certainty and avoid risks, reducing their chances of becoming early adopters and heavy users of new technologies (Akhter, 2003). Socioeconomic status is also a social locator (Atkin, Hunt, & Lin, 2015). However, our model treats it as a system factor because socioeconomic status is not independent of the macro-level systemic influence. Put differently, the social locators included in our model are innate attributes of individuals in contrast to the systemic factors that stem from social stratification. Therefore, the following hypothesis is stated:

H4a: The adoption of ride-sharing apps is positively related to the drivers' gender and age.

Regarding personality traits, audience factors are dispositional differences among the innovative attributes of individuals (Atkin, Hunt, & Lin, 2015). Innovativeness is an innate trait (Foxall & Bhate, 1991) that reflects the tendency toward novelty-seeking, self-actualization, openness to risks, and problem-solving (Hirschman, 1980; Lin, 1998; Rogers, 2003). Vishwanath (2005) described two dimensions of the innovative personality, both of which determine how an audience deals with uncertainty and the absorption of new information and practices. The first dimension is *global innovativeness*, which spans all human behaviors. It is defined as the degree to which an individual makes innovative decisions independently of social influence. Global innovativeness reflects some of the defining attributes of innovators (Rogers, 2003): adventuresome, novelty seeking, less risk-averse, and tolerant of complexity. This dimension is also related to the psychological trait of *openness to experience*, which is manifested in behaviors such as meeting new people, visiting new places, and seeking new information. The second dimension is context-specific innovation, which is an innovative behavior in a particular category. In this study, context-specific innovation involves technology use and is thus termed *technological innovativeness*. Previous empirical evidence suggested either the direct or the mediated influence of an innovative personality on technology adoption (Atkin, Neuendorf, Jeffres, & Skalski, 2003; Hunt, Lin, & Atkin, 2014; Li, 2013; Vishwanath, 2005). Therefore, the following hypothesis is stated:

H4b: The adoption of ride-sharing apps is positively related to drivers' global innovativeness.

> **H4c:** The adoption of ride-sharing apps is positively related to drivers' technological innovativeness.

Adoption Factors

According to the ITAP, adoption outcomes are layered, including non-adoption, discontinuance, likely adoption, actual adoption, and reinvention (Lin, 2003). These layers reflect the staged diffusion process described by Rogers (2003): diffusion starts when a person becomes aware of an innovation. In this process, the person is then motivated to try the innovation before finally deciding to adopt it. In the context of the present study, a driver may show interest in trying ride-sharing apps, yet his or her actual adoption might be delayed by certain barriers. Early adopters could possess distinct, individual attributes, and their early adoption could be the product of unique social and structural influences. Thus, the current study considers three adoption outcomes: actual adoption, early adoption, and likely adoption.

Methods

Sample selection

Figure 1 presents the adoption model tested in the study. A survey questionnaire was distributed to 1,195 taxi drivers in Beijing, China in the summer of 2014. The survey was conducted in Mandarin Chinese by trained facilitators. Data cleaning procedures were performed on the raw dataset to delete responses that did not include key demographic information (i.e., participants who did not provide their gender and age were excluded), which reduced the sample to 722 valid responses. The number of cases included in each model varied based on how many participants provided complete responses concerning all the studied variables included in a model.

Measures

Outcome variables. The model included three adoption outcomes. First, *actual adoption* was measured as a dichotomous variable, where 1 indicated adoption and 0 indicated non-adoption. Close to 80% of the surveyed taxi drivers were users of at least one ride-sharing app (556 of 722 cases), thus constituting the sample of adopters (n = 556). Among the remaining drivers, 30 chose not to disclose their adoption decision, which resulted in a nonadopter sample of 136. Second, *interest in adoption* (or likely to adopt) was measured by a survey item that asked how interested the participant was in using ride-sharing apps. The item applied only to the 136 non-adopters; their responses were averaged to form an index (mean = 2.41, s.d. = 1.10). Third, *the length of time since adoption*, which measured how early the 556 adopters had started using ride-sharing apps. Their answers were based on a five-point scale ranging from 1 (I have used a ride-sharing app for 0–3 months) to 5 (I have used a ride-sharing app for more than 13 months). On average, the adopters had used ride-sharing apps for at least half a year (mean = 3.77, s.d. = 1.23) at the time of the study.

Technology factors. Perceived usefulness was measured based on the average of the participants' responses regarding the perceived usefulness of ride-sharing apps in increasing revenue for their taxi business and efficiency in serving their customers (mean = 2.98, *SD* = .93). A single item was used to measure *perceived ease of use* (mean = 3.02, *SD* = .94). Regarding

Social factors. First, *word-of-mouth* was measured by three dichotomous items that asked whether the participant had heard of ride-sharing apps from colleagues (i.e., other taxi drivers), customers, and family members. The answers were summed to form a composite index (mean = .66, *SD* = .54). Second, *peer adoption* was measured by asking whether the participant's closest colleague was using a ride-sharing app (mean = 1.86, *SD*= .35). The third social factor was *subjective norm*, which was measured by two items adopted from Venkatesh and Davis (2000) (mean = 2.91, *SD* = .81).

System factors. Access to technologies was measured as the number of technological devices and services a participant had owned or used. The list included 10 widely used devices and services, such as tablets, smartphones, laptops, email, and online maps. The list also included products and services that are unique to the Chinese internet, such as the popular instant messaging apps WeChat and QQ and the Twitter-like micro-blogging app, Weibo. On average, the participants had used three of the 10 listed devices and services (mean = 3.44, *SD* = 2.75). *Digital literacy* was measured based on the participants' familiarity with a set of 14 technology-related terms (e.g., reload, blog, preference setting, proxy, PDF, jailbreak, etc.). The familiarity with each term was measured as a dichotomous outcome (1 = familiar, 0 = not familiar). The 14 answers were summed to form an index of digital literacy. This list of technology-related terms was adapted from Hargittai and Hsieh's (2012) original measure of digital literacy. Their measure was altered to reflect recent technological development and the idiosyncrasy of the Chinese internet. For example, the term jailbreak was listed because of its prevalent use among Chinese internet users. On average, the participants were familiar with fewer than three technology terms (mean = 2.83, *SD* = 3.58). Additionally, to measure *socioeconomic status*, the participants were asked about their income and educational attainment. The surveyed drivers had typically attained a high school education or less at the time of the study. They had a monthly income of RMB 2,501–5,000 (the equivalent of USD $367–$735), which is lower than the average income of RMB 6,500 in Beijing where the survey was conducted.

Audience factors. Global innovativeness was measured by an instrument adopted from Budner's (1962) study. The instrument was used to measure the average of the participants' answers to three survey items (mean = 3.06, *SD* = .81, alpha reliability =.81). The items asked the participants how comfortable they were in unfamiliar situations and locations and in dealing with strangers. *Technological innovativeness* was measured by two items adapted from Goldsmith and Hofacker's (1991) work. The participants' answers to the two items were averaged to form an index (mean = 3.08, *SD* = .91). All survey items were based on a five-point response scale that ranged from 1 = strongly disagree to 5 = strongly agree. The participants were asked to state their age and gender. The sample of 722 participants was comprised of predominantly male drivers (513 males, 209 females), which reflected the gender distribution reported in a previous study on Chinese taxi drivers (Nielsen et al., 2010). The average age of the surveyed drivers was 44 years.

Control variable. The number of years in the taxi industry was measured as the control variable. The surveyed participants had spent an average of three years in the taxi industry at the time of the survey. The measures used in the study are described in detail below.

Overview of Models

A set of regression models was constructed using each of the three adoption outcomes. The first was a logistic regression model, which was applied to all participants who had provided complete responses to all variables. This model was applied to predict the dichotomous outcome of adoption or non-adoption. The second model, which was based on the sample of adopters, predicted the length of time since adoption. The third model, which was based on the sample of non-adopters, predicted their interest in adopting the app. The independent variables in the models pertained to the control variable as well as the four groups of factors outlined in the literature review: technology and use, social, system, and audience. A different set of models was required to test H3c and H3e. In the models, digital literacy and access to technologies were used as the outcome variables. Socioeconomic status (i.e., income and education attainment) were the key predictors, and demographic factors (i.e., age and gender) were the control variable. Figure 1 shows the models and the hypotheses.

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Results

We first tested the model using the dichotomous outcome of actual adoption as the dependent variable. A logistic regression was performed, which yielded significant results (see Table 1): $\chi 2 = 146.33$ ($p<.001$). The Cox and Snell was $R^2 = .25$, indicating that the model performed well. Regarding the technology and use factors, perceived usefulness had a positive relationship with actual adoption ($\beta = .69$, $p <.01$). Concerning the social factors, peer adoption ($\beta = .86$, $p <.01$) and word-of-mouth ($\beta = .63$, $p <.01$) were positively related to adoption. ~~Regarding the system factors, income had a positive relationship with adoption (β = .47, p <.05).~~ However, system factors do not predictive of adoption. Lastly, regarding the audience factors, age was negatively associated with actual adoption ($\beta = -.51$, $p <.01$), showing that younger taxi drivers were more likely to adopt ride-sharing apps. Technological innovativeness was positively related to adoption ($\beta = .48$, $p <.01$). However, another dimension of the innovative personality—global innovativeness—negatively predicted adoption ($\beta = -.46$, $p <.05$). The findings from this model supported H1a, H2a, H4c and partially supported H3a and H4a.

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The second model was applied to the sample of adopters. A regression was conducted on the outcome variable of the length of time since adoption. Cases with missing values of the study variables were excluded (see Table 2). The findings from the final model were significant: F (14, 393) = 3.97, $p <.001$, which explained 9% of the variance in the length of time since adoption. Access to technologies was positively associated with the length of time since adoption ($\beta = .31$, $p <.001$). More experienced drivers (based on the number of years in the taxi industry) were more likely to be early adopters ($\beta = .13$, $p<.05$). The findings from this model support H3b.

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The third model was applied to predict the interest in adoption among the non-adopters (Table 3). This model had a small sample size because the number of non-adopters was much smaller among the surveyed drivers (valid cases = 63). The findings of the final model were significant: F (14, 48) = 2.14, $p<.05$, which explained 21% of the variance in the outcome variable. Although none of the predictors was significant at the .05 level, the small sample size may have led to a type two error. Therefore, it is important to focus on the predictors that achieved significance at the .1 level. Among the non-adopters, interest in adoption was positively predicted by subjective norm ($\beta = .27$, $p <.1$) and word-of-mouth ($\beta = .25$, $p <.1$).

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A different set of models was required to test H3c and H3e (Table 4). Two models were applied to the sample, which included both adopters and non-adopters. First, the access to technologies was entered as the outcome variable, which was predicted by gender, age, educational attainment, and income. Based on the cases with complete responses, the model was significant: F (4, 696) = 17.86, $p<.001$, which explained 9% of the variance in the outcome variable. Younger (β = -.13, p <.001), more educated (β = .22, p <.001), and more affluent drivers (β = .12, p <.05) tended to use more technologies. Using the same set of predictors, but with digital literacy as the outcome variable, the findings of the model were significant: F (4, 696) = 12.71, which explained 6% of the variance in the outcome variable. The results showed that more educated drivers (β = .17, p <.001) and younger drivers (β = -.16, p <.001) had higher levels of digital literacy.

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Discussion

In this study, the integrated technology adoption model was applied to explore the association of various antecedents with the adoption of ride-sharing apps by Chinese taxi drivers in Beijing. The inclusion of various technologies and their use as well as social, audience, and system-related factors enabled us to determine whether the sharing economy, which was represented by the ride-sharing apps, would potentially alleviate or replicate social inequality. In the study, we hypothesized that system factors stemming from existing social inequalities, such as drivers' varying levels of wealth, knowledge, skills, and experience, could present barriers to innovation diffusion, thus limiting their opportunities in the sharing economy. Our findings provided mixed support for this hypothesis. In this section, we discuss the study's findings in order of the four components of the antecedents identified by ITAP.

The factors of technology and use played a salient role in the adoption. The surveyed adopters indicated a utilitarian view of the technology. Their responses indicated that in their adoption decision, they considered the app's perceived functions of attracting customers and increasing efficiency. However, different from previous findings (Davis, 1989), our results showed that the cost of adoption and the perceived complexity of the technology were inconsequential. A possible explanation for this finding is that the adoption of a ride-sharing app is neither labor-intensive nor risky. Interestingly, a significant association between perceived usefulness and adoption was found only in the sample of the adopters. Regarding the non-adopters in our study, technology factors were positively but not significantly related to their interest in adoption, which may have been due to the small sample of non-adopters. It is also plausible that the adopters, because of their experience with the app, had developed a different and perhaps more accurate perception of the technology compared to the non-adopters.

Social factors showed the greatest influence on actual adoption, which was demonstrated by the effect size of the variables of peer adoption and word-of-mouth in the model. The two social factors may have also influenced the interest in the adoption of the app by non-adopters. This finding is in line with the results of previous studies that emphasized the importance of social influence (Lin, 2003). The insignificant role of the variable of subjective norm in the model might be because ride-sharing apps are used for functional purposes rather than for impression management or relationship development. This finding indicates that although making a good impression on customers and peers is essential, this factor alone is not necessarily included in adoption decisions.

The findings concerning the system and audience factors have rich implications for social inequality in the sharing economy. In this study, we compared and contrasted two different forces: innate forces, which are exemplified by audience factors, including innovative personality trait, age, and gender; and structural forces including income, education attainment, and the digital divide. Previous studies showed that social inequality was the source of digital inequality (Litt & Hargittai, 2014). The taxi drivers surveyed in our study scored relatively low on digital literacy (2.83 on a scale of 14). The drivers who used ride-sharing apps were more digitally literate than the non-adopters were. Their comparatively higher digital literacy was linked to the ownership of more digital gadgets and the use of more services. Indeed, digital literacy and access to technologies were highly correlated at r = .72. Because of the strong correlation between access to technologies and digital literacy, in the following interpretation we consider them two aspects of the digital divide.

The system factors appeared to have step-wise effects on the diffusion of ride-sharing apps. In early adoption, the digital divide is a salient factor. However, at the time of the survey, the majority of the surveyed taxi drivers owned a smartphone (79%) and had used ride-sharing apps, indicating that the diffusion of ride-sharing apps had reached the later stage. ~~Thus, in the later stage of the diffusion, socioeconomic factors (income) emerged as more pronounced than the digital divide.~~ One possible explanation is that when ride-sharing apps were first launched, because of their novelty, their adoption was constrained by technical barriers. However, as the apps gradually became popular, their perceived technological sophistication was reduced and was no longer a barrier to adoption. The findings also indicate that socioeconomic disadvantages are closely linked to the digital divide. The taxi drivers who were more affluent and more educated than others were also better digitally equipped and skilled. This finding may support the path of influence reported in the prior digital literature: existing socioeconomic inequality first affects the digital realm, resulting in the digital divide (Park, 2015), and then it influences adoption decisions (Hargittai & Litt, 2012). In addition to the structural factors in the digital divide, adoption is associated with innate personality traits, particularly in the late stage of adoption. However, it does not necessarily drive early adoption. As noted earlier, technological barriers could be more discouraging in the early stage of diffusion. As a new technology becomes increasingly well-known, its technological barriers fade, but several innate dispositional factors are left to discourage adoption.

In summary, concerning how the sharing economy affects the wellbeing of the underclass in a rapidly digitalizing society, the findings of the present study revealed that multiple forces shaped the adoption of ride-sharing apps by the taxi drivers surveyed in Beijing. System factors, which have long been considered the source of inequality, are undoubtedly salient and require attention. Notably, the findings of our study demonstrated that socioeconomic and digital inequality are intertwined. However, the unevenness of technology adoption might also be an outcome of demographic and dispositional differences as well as social influence.

The study contributes to the discussion on the economic and societal effects of the sharing economy. To the best of our knowledge, this study is one of the first to discuss such effects using empirical data. It is also one of the few studies that investigated the specific case of the adoption of the ride-sharing app. Our innovative approach connects the latest technology adoption models to the effects of the sharing economy. Moreover, our findings yielded several practical insights. In the sharing economy, app diffusion is driven mainly by social influence. Thus, in promoting new technologies to those who need the technologies the most, identifying innovators and opinion leaders could be a critical pathway to fast diffusion.

Limitations and Future Directions

This study has several limitations. First, the model using the cases of non-adopters was applied to a small sample, which leaves room for the type two error; that is, a significant relationship was undetected in the model. Second, the key variables in the study were measured by a small number of survey items (2 or 3 items), which raises concerns about reliability. Third, because adoption is a temporal process, the current data did not distinguish the order of the time of adoption, which made the interpretation of the causal effects difficult, if not impossible. Lastly, although the survey was conducted in Mandarin Chinese, several survey items on the key variables were adopted from research published in English. Thus, the translation from English into Mandarin Chinese may have created a bias.

We encourage scholars to continue research on the potential disenfranchizing effects of the sharing economy. Although ride-sharing apps might be easy to use and thus present no real skill barrier, future studies could investigate the adoption of apps that require a sophisticated understanding of technology and its usage. Future studies could also use a longitudinal design to examine the causal effects of several factors related to social stratification, social influence, personality traits, and technological characteristics. Moreover, focus-group interviews might also reveal the thought process that leads to adoption.

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The author(s) declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Notes on contributors

Xinchuan Liu, PhD, is an Assistant Professor in the School of Journalism and Communication at Peking University, China. Dr. Liu is a research fellow in the Center for Crisis Management Research (sponsored by Beijing Planning Office of Philosophy & Social Science) and the Director of Academic Department, National Institute of Strategic Communication, Peking University. His research focuses on new media and communication theory, new ICTs and social change.

Weiai (Wayne) Xu, PhD, is Assistant Professor in the Department of Communication at University Massachusetts – Amherst. His research focuses on the role and effects of technology on the flow of information, values, behaviors, and resources in empowering civil societies.

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Tables

Table 1. A Logistic Model for Predicting Adoption

		β	S.E.	Wald
Technology and use factors	Perceived usefulness	.69**	0.23	8.79
	Perceived ease of use	-0.07	0.24	.1
Social factors	Word-of-mouth	.63**	0.19	11.5
	Subjective norm	0.04	0.18	0.06
	Peer adoption	.86**	0.14	36.52
System factors	Education attainment	-.30$^{\#}$	0.16	3.5
	Income	.27	0.18	2.35
	Digital literacy	0.13	0.28	0.21
	Access to technologies	0.28	0.27	1.06
Audience factors	Gender	-0.04	0.56	0.004
	Age	-.51**	0.73	5.69
	Global innovativeness	-.46*	0.19	5.86
	Technological innovativeness	.48**	0.20	6.08
Control	Years in industry	.34$^{\#}$	0.18	3.41

Note. $^{\#}p <.10$(two-tailed), * $p <.05$ (two-tailed), ** $p <.01$ (two-tailed); $\chi 2 = 146.33$ ($p <.001$), $R^2 = .35$ (Hosmer–Lemeshow), .25 (Cox–Snell)

Table 2. A Regression Model for Predicting Time Since Adoption among Adopters

		β	S.E.
Technology and use factors	Perceived usefulness	-0.01	0.09
	Perceived ease of use	-0.08	0.09
Social factors	Word-of-mouth	0.05	0.11
	Subjective norm	-0.06	0.08
	Peer adoption	-.08[#]	0.26
System factors	Education attainment	0.05	0.06
	Income	-0.06	0.1
	Digital literacy	-0.02	0.02
	Access to technologies	.31**	0.03
Audience factors	Gender	-0.01	0.21
	Age	-0.03	0.01
	Global innovativeness	-0.03	0.08
	Technological innovativeness	0.07	0.08
Control	Years in industry	.13*	0.08
***F*, Adj. R^2**		F (14, 393) = 3.97, .09**	

Note. # p <.10(two-tailed), * p <.05 (two-tailed), ** p <.01 (two-tailed)

Table 3. A Regression Model for Predicting Interest in Adoption among Non-Adopters

		β	S.E.
Technology and use factors	Perceived usefulness	0.24	0.26
	Perceived ease of use	0.11	0.27
Social factors	Word-of-mouth	.25#	0.25
	Subjective norm	.27#	0.17
	Peer adoption	0.07	0.29
System factors	Education attainment	0.05	0.16
	Income	0.02	0.3
	Digital literacy	0.01	0.07
	Access to technologies	-0.2	0.07
Audience factors	Gender	0.19	0.47
	Age	-0.11	0.02
	Global innovativeness	-0.11	0.18
	Technological innovativeness	-0.01	0.2
Control	Years in industry	0.12	0.2
	F, Adj. R^2	*F* (14,48) = 2.14, .21*	

Note. #p <.10(two-tailed), * p <.05 (two-tailed), ** p <.01 (two-tailed)

Table 4**. Regression Models for Predicting Access to Technologies and Digital Literacy**

	Access to technologies		Digital literacy	
	β	S.E.	*β*	S.E.
Gender	-0.03	0.37	-0.03	0.5
Age	-0.13**	0.01	-0.16**	0.02
Education	0.22**	0.11	0.17**	0.15
Income	0.12*	0.17	0.06	0.23
F, Adj. R^2	F (4,696) = 17.86, .09***		F (4,696) = 12.71, .06***	

Note: #p <.10(two-tailed), * p <.05 (two-tailed), ** p <.01 (two-tailed)

Figure

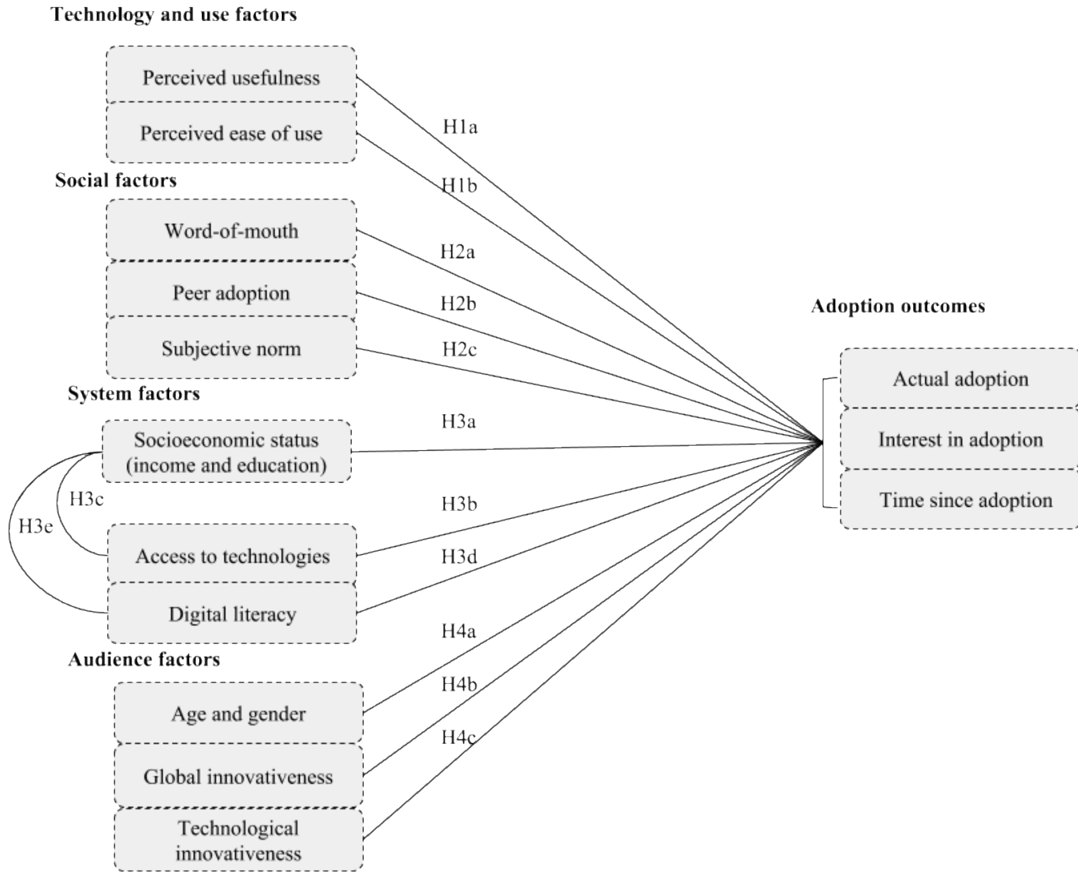

Figure 1. The integrated adoption model